

FACTORS AFFECTING INCOME INEQUALITY IN
DEVELOPING COUNTRIES

BY

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LIST OF ABBREVIATIONS

GINI	GINI coefficient/ Income Inequality
EL	School enrollment tertiary
CC	Corruption
GL	Globalization
FDI	Foreign direct investment
lFDI	Log Foreign direct investment
GDP	Gross domestic product per capita
lGDP	Log Gross domestic product per capita
UR	Unemployment rate
BP LM test	Breusch and Pagan Lagrange Multiplier test
POLS	Pooled Ordinary Least Square
REM	Random Effect Model
FEM	Fixed Effect Model
PCSE	Panel-corrected Standard Error

PREFACE

In the study, factors affecting income inequality in developing countries, one might address the profound implications of income inequality on both economic growth and social stability. It could be emphasized that while economic growth is often a primary objective for developing nations, the distribution of income within these economies is equally crucial for sustainable development and income inequality.

Factors include education enrollment, globalization, corruption, GDP per capita, FDI inflows and unemployment rate. Moreover, the preface could stress the importance of rigorous research and analysis in understanding the root causes of income inequality and formulating effective policy interventions.

Overall, the preface sets the stage for a comprehensive exploration of the factors driving income inequality in developing countries, emphasizing the urgency of finding sustainable solutions to promote income equalize.

Abstract

This paper investigates factors affecting income inequality in 33 developing countries from 2015 to 2020. The factors include education level, corruption, globalization, foreign direct investment inflow (FDI) and GDP per capita. However, the unemployment rate is considered as a control variable. Nevertheless, the interaction effect between foreign direct investment inflow and GDP per capita on income inequality is substantial in these countries. Meanwhile, the empirical findings of Panel Corrected Standard Error (PCSE) indicate that FDI inflows and GDP per capita are significant determinants of increasing income inequality. FDI inflows and GDP per capita are essential in moderating the income inequality, especially in increasing the income gap when countries' inequality is lower; however, other variables show insignificant between income inequality.

Chapter 1: Research Overview

1.0 Introduction

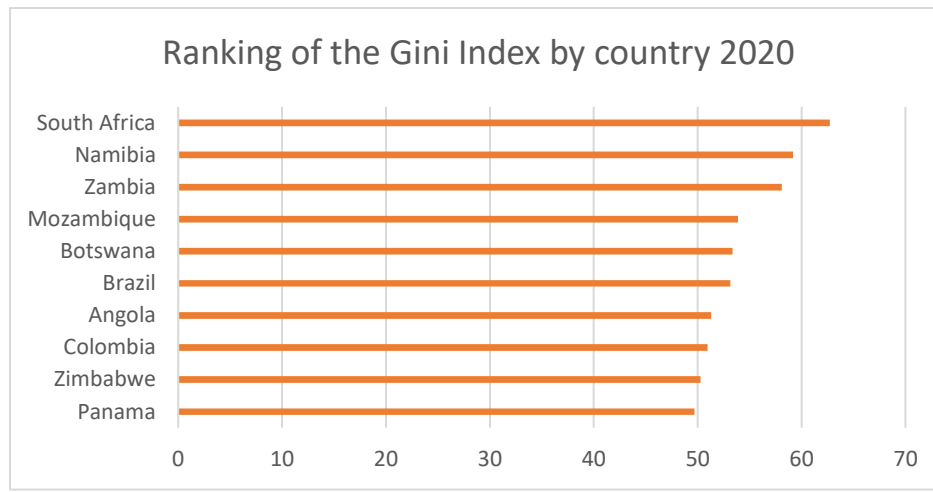
Chapter one of this study will comprise eight sections aimed at providing a comprehensive understanding of income inequality in developing countries such as research background, problems, questions, objectives, hypotheses, significance of study, chapter layout and a short conclusion. The study overview section will provide readers with a broad perspective on the prevailing income disparities across the region. Over the two decades, the influence of factors such as education levels, globalization, corruption, foreign direct investment and gross domestic per capita on income inequality in developing countries has been a focal attention. This chapter seeks to shed light on the various issues that contributed to income inequality during this period, providing insights into the complex link of socioeconomic dynamics shaping the region's economic landscape.

1.1 Research Background

According to Kopp (2023), income inequality refers to the unequal distribution of income within a population. The degree of income inequality increases with distributional inequality. To illustrate various degrees and manifestations of income inequality, such as disparity by gender or race, populations can be segmented in a variety of ways. A variety of metrics, including the Gini Index, may be employed to assess the degree of income disparity within a given population. Everyone is perfectly equal when there is no variance, as shown by a score of 0 on the index. A score of 100 signifies complete inequality; a single individual possesses all the country's riches. Compared to developed countries, developing countries often have greater rates of income inequality (Derviş & Qureshi, 2016). Over the last three decades, income inequality increased in the majority of significant rising economies. The developing

world presents a more varied image. Until 2020, based on the ranking of the Gini index by country 2020, the top ten highest Gini coefficient countries all belong to developing countries (Figure 1).

Figure 1.1: Ranking of Gini Index by 2020



Source: Statista. (2023). Gini index worldwide 2020, by country.

However, in the two decades prior to the COVID-19 epidemic, developing countries had steady growth, which made it possible to achieve much-needed progress in reducing poverty (Cugat & Narita, 2020). Now, a great deal of that progress is in jeopardy as the crisis deepens the divide between the affluent and the poor. Many of these nations have had difficulty reducing income inequality, notwithstanding their pre-pandemic accomplishments in reducing poverty. In addition, they observed continually high rates of young inactivity which youth without jobs, degrees, or training as well as significant educational disparity.

There have different factors affecting income inequality in developing countries such as globalization, corruption, educational attainment, foreign direct investment, gross domestic product per capita and others. One important factor that significantly influences socioeconomic position and income is education. Higher education often

translates into more earning potential and easier access to possibilities for skilled work. Nonetheless, differences in educational access and quality continue to exist in many developing nations, which feeds into income inequality. Marginalized populations, such as those who are impoverished or who reside in underprivileged areas, frequently encounter obstacles to education, such as inadequate infrastructure, cultural norms, and gender discrimination.

According to Tabash et al. (2024), globalization has increased inequality and led to the marginalization of the poor masses in developing countries. Many countries in the region have experienced significant economic growth and development as a result of the growing interconnectedness of the global economy. However, the advantages of globalization have not been shared equally, with some people and companies benefiting while others have been left behind. For example, by increasing the importation of manufactured products made mostly with low-skilled labor from developing nations, globalization can raise pay disparity in a relatively prosperous country (Hauk & Hauk, 2019). There is a chance that technological advancement may make salary disparities worse. If computers and automation take the position of secretaries, typists, and assembly-line workers in the manufacturing process, fewer of these individuals will be required. On the other hand, more advanced technology may make it more necessary for engineers, for example, to service those devices. Therefore, it increases export prospects in high-tech companies that employ a greater number of highly qualified workers. The difference in pay between highly and less skilled individuals may grow as a result of these two factors.

As a result, the income gap has widened as those who can profit from globalization continue to amass more wealth and money. However, in developing countries, informality actually amplifies the same labor market forces: individuals with lower skill levels who work mostly informally are not eligible for unemployment benefits or furlough programs (Inequality and COVID-19 – IMF F&D, 2021). Due to the Covid-19 epidemic, hundreds of millions of these workers had to make the very difficult decision every day between keeping safe at home and risking illness to feed their family.

Another significant element that raises income disparity in developing countries is corruption. Officials and institutions within the government divert public funds away from essential services like healthcare and education when they participate in corrupt activities like bribery and embezzlement (Transparency International, 2021). Furthermore, there is a lot of corruption in the run-up to elections. In the last five years, about one in seven persons has received offers of bribes in return for their votes in a municipal, regional, or national election (Transparency International, 2021). Despite claims of rampant vote-buying in the Maldives, particularly during parliamentary elections, no case has been brought to court thus far. According to Transparency International (2021), nearly 20% of people resort to expediting official documents like driver's licenses and birth certificates and leverage familial or social connections to skip queues and gain easier access to hospitals and schools, often resorting to bribery. Almost one in five individuals who accessed public services in the past year resorted to bribery, with India leading at 39%, followed by China at 36%, and Indonesia at 32%. Conversely, only 4% of public service users in Cambodia respectively, relied on personal connections (Transparency International, 2021). This causes inequality by weakening social safety nets and reducing chances for the most disadvantaged segments of society.

Foreign direct investment (FDI) can greatly affect a country's income inequality. Foreign investors often provide or exchange knowledge and technology to a country, which can promote job creation and economic progress. Therefore, foreign direct investment has the potential to reduce income inequality by raising workers' wages and promoting overall economic growth (Yuldashev et al., 2023). However, FDI is allocated may vary based on factors such as the investment industry and the skill level of the workforce. This is because foreign investors will choose the potential industries and skilled workers to invest. At the same time, there are also disadvantages if foreign direct investment (FDI) primarily benefits skilled workers or encourages labor exploitation in low-wage industries, it may in some cases exacerbate income disparities. In addition, income distribution may be affected by government measures to attract foreign direct investment (FDI), such as reduced taxes and deregulation for foreign investors.

A country's GDP is also determined by dividing its total population by its GDP per capita. (Team, 2024). Based on a nation's rate of economic growth, GDP per capita is used by economists to assess that nation's prosperity and population's standard of living. Countries with smaller populations and more industrialized and developed countries generally have higher GDP per capita. Countries with higher GDP per capita tend to have better infrastructure, better employment opportunities, social security, and economic development, all of which can reduce income inequality. However, there is a complicated link between GDP per capita and income inequality such as how people revenue is distributed across the population and how well social welfare programs work. Although reductions in income inequality are typically associated with increases in GDP per capita, considerable differences in income distribution may remain in some high-income countries for numerous socioeconomic factors.

In summary, many factors affect income inequality in developing countries, including education level, globalization, corruption, foreign direct investment, and gross domestic product per capita. Many actions had been made to reduce income inequality before the COVID-19 pandemic; however, the crisis has once again widened the gap between rich and poor. For example, globalization has led to widening income gaps, and corruption has deprived people of welfare funds. Therefore, governments need to put more efforts in order to eliminate corruption, increase educational opportunities to solve these complex problems.

1.2 Research Problem

Even with notable advancements in educational attainment in developing countries such as Argentina, Chile, and others, socio-economic growth is nevertheless beset by the enduring problem of income inequality. According to the World Bank (2023), Argentina and Chile have consistently maintained high levels of income inequality despite consistently high tertiary enrollment rates, with their school enrollment, tertiary (% gross) always around 90 and above in years 2017 to 2020. This is demonstrated by their Gini index values consistently above 40 between 2015 and 2020. However, this is

only a few developing countries are chosen as example, therefore there still many developing countries in Bulgaria, Turkiye and others that face the same issues.

In most developing nations, there is a dearth of digital infrastructure, and access to what is available varies according to socioeconomic level. For example, technology especially in India might not reach remote or rural areas, while the impoverished in urban areas might not have the resources to fully engage (Jayant Menon, 2021).

Given that automation and robots first proliferate in low- and mid-skilled occupations, the danger to their jobs is particularly significant. This raises the chance of unemployment for jobs in the low to mid-skill levels. Not only that, Costa Rica, and Argentina also face some issues in which they have high globalization but consider significant income inequality. From 2015 to 2020, Costa Rica remained its KOF globalization about 80 but Gini index around 50. Moreover, Argentina has about 75 KOF globalization index for Gini index is around 40 along 6 years.

Corruption remains a widespread problem in many developing countries, with negative effects on economic development, governance systems and social well-being. Corruption can lead to misallocation of resources and divert important public funds away from basic services and infrastructure projects, keeping countries in a cycle of underdevelopment and inequality or even exacerbating it. This failure in anti-corruption not only undermines people's trust in government institutions, but also exacerbates socioeconomic disparities, as some elites sacrifice the hard-earned wealth of the majority for their own benefit. When measuring perceived levels of corruption worldwide, the Corruption Perceptions Index (CPI) often finds worrying ratings for many developing countries. According to the CPI, 180 countries are ranked according to how corrupt the public sector with a score ranging from 0 which means extremely corrupt to 100 which is very clean. For example, in 2020, countries such as Colombia get a score of 39 (ranked 92th), Brazil get 38 (ranked 94th), therefore, they may face high corruption and cause income inequality, although both of the countries have high school enrollment. Not only that, Dominican Republic get 28 (ranked 137th), and El Salvador get a score of 36 (ranked 104th). Notably, no one of developing country

managed to get top 10 of the CPI rankings in 2020, therefore it show the widespread nature of corruption within these regions.

When compared to other nations, developing countries can attract FDI although face high income inequality. For example, Brazil and Colombia have both drawn sizable levels of foreign direct investment (FDI), despite having high Gini index values. At first, this may appear paradoxical because there is occasionally a correlation between excessive income disparity and unstable economies or adverse business conditions. According to data from the World Bank (2023), both countries' FDI inflows are substantially higher than other countries however Gini index value maintains 50 and above. Therefore, there are other forces at work, even while historically high-income disparity may indicate economic instability or bad business circumstances.

Results of journals or articles sometimes have positive and also negative relationships which means contradicting results in education level, globalization, corruption, foreign direct investment and gross domestic product per capita to income inequality.

1.3 Research Questions

1.3.1 General Question

What is the impact of factors affecting income inequality in developing countries?

1.3.2 Research Specific Questions

- i. What is the impact of education level affecting income inequality in developing countries?
- ii. What is the impact of globalization affecting income inequality in developing countries?
- iii. What is the impact of corruption affecting income inequality in developing countries?

- iv. What is the impact of foreign direct investment affecting income inequality in developing countries?
- v. What is the impact of gross domestic product per capita affecting income inequality in developing countries?

1.4 Research Objectives

1.4.1 General Objectives

To investigate the factors affecting income inequality in developing countries.

1.4.2 Research Specific Objectives

- i. To investigate the impact of education level affecting income inequality in developing countries.
- ii. To investigate the impact of globalization affecting income inequality in developing countries.
- iii. To investigate the impact of corruption affecting income inequality in developing countries.
- iv. To investigate the impact of foreign direct investment affecting income inequality in developing countries.
- v. To investigate the impact of gross domestic product per capita affecting income inequality in developing countries.

1.5 Hypotheses of the Study

H_{01} : There is no significant relationship between education level and income inequality in developing countries.

H_{A1} : There is a significant relationship between education level and income inequality in developing countries.

H₀₂ : There is no significant relationship between globalization and income inequality in developing countries.

H_{A2} : There is a significant relationship between globalization and income inequality in developing countries.

H₀₃ : There is no significant relationship between corruption and income inequality in developing countries.

H_{A3} : There is a significant relationship between corruption and income inequality in developing countries.

H₀₄ : There is no significant relationship between foreign direct investment and income inequality in developing countries.

H_{A4} : There is a significant relationship between foreign direct investment and income inequality in developing countries.

H₀₅ : There is no significant relationship between gross domestic product per capita and income inequality in developing countries.

H_{A5} : There is a significant relationship between gross domestic product per capita and income inequality in developing countries.

1.6 Significance of the study

The significance of the study lies in its potential to provide light on the complex problem of income inequality in the developing countries setting. The objective of this research is to identify complex problems that can guide policy interventions and social solutions by exploring the complex interactions among education level, globalization, corruption, foreign direct investment and GDP per capita as variables influencing income distribution.

First, by pinpointing and comprehending the main causes of income disparity, this research may provide policymakers with useful information. Utilising this knowledge to assist in the creation of approach-oriented as well as practical policies may lead to a reduction in economic inequality and the promotion of social fairness. Initiatives to expand educational opportunities, increased effectiveness of the fight against

corruption, promotion of foreign direct investments, GDP per capita maintenance on the level and promotion of economic growth within the country programmes.

Additionally, the study's contribution to academic literature is essential for furthering our understanding of the complex interactions among factor such as income inequality, education, globalization, corruption, foreign direct investment and GDP per capita affecting income inequality in developing countries. Empirical data, and theoretical ideas that are examined will push researchers towards creating both frameworks and tools that can help study the mechanisms of income distribution more smoothly.

From perspective of investor, the study is important because it can offer insightful information on the economic conditions of developing nations, especially with regard to the causes and dynamics of income disparity. International and domestic businesses owners and traders will always think about the profits and risks of their investments, as well as the differences of various markets and economy sectors. Knowledge about the income distribution of emerging economies enables individuals to develop more reasoned investment tactics and to be able to estimate the risk of their decision adequately.

Finally, this study project has the potential to significantly advance academic research, wise decision making of investor and useful policymaking. This study intends to stimulate positive change towards more equitable and inclusive communities by bringing light on the intricate dynamics of income inequality and its drivers throughout developing countries.

1.7 Chapter Layout

1.7.1 Chapter 1

The study is divided into five chapters, each organized with the background as the main idea. It explores the factors affecting income inequality in developing countries. In addition to addressing the background, the study specifies the problem statement, significance of study and hypotheses. Research questions and objectives are included in this chapter along with additional subtopics to help improve understanding of the problem of income inequality in developing countries.

1.7.2 Chapter 2

The study's chapter structure on the factors affecting income inequality in developing countries with a comprehensive literature review, delves into relevant theoretical models. A proposed conceptual framework synthesizes insights from the literature and theoretical perspectives to illustrate the relationships between the variables.

1.7.3 Chapter 3

Chapter 3 consists of research methodology on factors affecting income inequality in income inequality. It has covered research design, data collection methods, research instruments, data processing and others. This chapter will also explain the models and analysis tests in the study, to examine the relationship between the dependent variable which is income inequality and independent variables which are education level, corruption, globalization, GDP per capita and foreign direct investment.

1.7.4 Chapter 4

In chapter 4, it consists of descriptive analysis, scale measurement, model evaluation and diagnostic test. Based on these analyses, it will provide a more comprehensive understanding based on results.

1.7.5 Chapter 5

In chapter 5, it consists of a summary and discussion of major findings to provide a precise and clear understanding of the research. Not only that, implications, limitations and recommendations can provide governments, investors and further researchers as references.

1.8 Conclusion

In short, the first chapter introduces the factors of income inequality in developing countries and deeply discusses the background of income inequality in developing countries, research problems, research questions, research objectives, research significance and hypotheses. Therefore, this chapter serves as the basis for research. People first understand the factors that cause inequality, and then governments, academics and investors work together to make the country equal.

Chapter 2: Literature review

2.0 Introduction

The literature review will be covered in this chapter. The theoretical models, conceptual framework, model specification and research gap will also show how the relationship between dependent and independent variables. It would be more clearer after understanding the correlation between income inequality and other independent variables.

2.1 Literature Review

2.1.1 Income Inequality

According to Zandi et al. (2022), the study is to examine the dynamic effects of inflation, unemployment, and corruption on income disparity is the goal of the study. There have 15 years of balanced panel data from 2006 to 2020 of 12 emerging Asian nations were used for this research. The link between the chosen variables is investigated using the Generalized Method of Moments (GMM) and the Random Effect Model (REM). According to the findings, unemployment, inflation, and corruption have significant and positive relationships with the GINI index therefore raising levels of income inequality in developing Asian nations. The findings show that these Asian countries face income inequality due to rise in corruption, inflation and unemployment.

This study is to examine the foreign direct investment (FDI) effect on income inequality was between 1980 and 2013 in a panel of sixteen African nations (Kaulihowa & Adjasi, 2017). Pooled Mean Group estimator was used to account for heterogeneity as well as non-linear effects and it has strong evidence of a non-linear relationship and a U-shaped impact of FDI on inequality. The findings show that FDI improves income distribution equality in the nations under investigation. Nevertheless, when FDI rises further, this effect becomes less pronounced. The study's policy implications suggest that FDI must target both ends of the labour market to address inequality.

According to Saha et al. (2021), the study shows that even in Asia countries with robust anti-corruption measures, the existence of shadow economies contributes to increased inequality. Underpinned by static and dynamic panel data analyses of 21 Asia countries from 1995 to 2015, the ability to translate secondary and tertiary school enrolment into industrial and, more crucially, service sector jobs is a necessary complement to corruption control in the fight against rising inequality. Investing more on public consumption can help nations with low levels of corruption and high levels of

inequality to become less unequal. Moreover, less corruption and increased commercial openness reduce inequality, except in South Asian nations.

This study investigates the connection between income inequality and economic complexity (Chu & Hoang, 2020). This research uses two estimating approaches and panel data on eighty-eight nations from 2002 to 2017 to establish a substantial relationship between economic complexity and increased income disparity. The findings offer circumstantial evidence that the positive effects of more economic complexity on lowering income disparity are facilitated when levels of trade openness and education approach particular thresholds. On the other hand, economic complexity is unsuccessful at reducing income disparity in settings with poor economic openness and low levels of education. The research has implications for how governments can modify their approaches to address inequality as they work to create a knowledge-based economy.

According to Erauskin and Turnovsky (2022), both financial globalization and income inequality have significantly increased between 1970 and 2015 in higher income countries. Overall, the findings are consistent with the hypothesis that rising income disparity is a product of financial globalization. Additionally, lowering borrowing rates will have less of an effect on inequality than lowering the cost of foreign investment. Regarding the effect of trade liberalization on income disparity, the results are less conclusive, although the quintile data results support the idea that trade liberalization lowers income inequality.

2.1.2 Education level

This study offers proof that the distribution of income is significantly influenced by human capital, as indicated by educational attainment (Lee & Lee, 2018). For the years between 1980 and 2015, regressions using panel data for a wide range of countries demonstrate how a more equitable distribution of education has significantly reduced income inequality. A higher level of education also contributes to a decrease in income

inequality by reducing educational inequality. The empirical data also reveals that in order to improve income and education distribution, there should be more public investment in education, reduced inflation, and increased social benefit expenditures. However, Lee and Lee (2018) found that the average number of years spent in school may have a positive or negative impact on income inequality, depending on how the rates of return on education have changed over time.

The premise of this study is that there is a quadratic link between education and income disparity (Arshed et al., 2018). This study analyzes panel data from 1990 to 2015 to assess it for the South Asian Association for Regional Cooperation (SAARC) nations, which include Afghanistan, Bangladesh, Bhutan, India, Maldives, Nepal, Pakistan, and Sri Lanka. The long-run panel data required the use of a panel co-integration method, which was then followed by the generation of long-run coefficients using a completely modified OLS model. The findings show that higher education enrollment significantly reduces income disparity. This implies that as postsecondary education levels rise, income disparity will decline.

According to Ajide and Alimi (2021), this study examines the relationship between income inequality and terrorism using four different markers: total, uncertain, transnational, and domestic, respectively, and mediated by the function of human capital across a panel of 34 African nations between 1980 and 2012. Because of the frequency of zero values in the terrorist data, this study further uses a zero-inflated negative binomial regression estimator rather than providing correlation analyses suggested by exploratory analytics across these main variables of interest. At increasing levels of educational attainment, there are negative marginal implications of interactions between indices of income inequality and human capital measurements. These results hold up well when endogeneity issues, country- and time-specific effects, alternative estimators, and geographical impacts are taken into account.

For the years 1960 to 2015, this study develops a quadratic relationship between education and income inequality among Asian developing economies (Arshed et al.,

2019). The estimate of long-run coefficients uses panel cointegration and completely modified OLS. By providing a thorough understanding of the effects of various levels of educational attainment on income disparity in the context of Asian countries, this study adds to the body of knowledge already available on the link between tertiary enrolment and income inequality. The results show that there is a link between tertiary enrolment and income disparity that is dependent on enrollment levels. Therefore, an increase in tertiary enrollment is observed to intensify income inequality initially. This is because those with more education expect to get a higher salaries, which widens the income gap (Arshed et al., 2019).

According to Abolfazl et al. (2018), the study examines the impact of income disparity in a few Islamic nations between 1990 and 2013. The panel data method has been used to run the test. Moreover, the Hausman test is used to compare the fixed effects to the random effect. Tertiary education on income disparity is examined in the chosen Islamic nations during this study. The results show that there is a positive and significant relationship between tertiary education school enrollment and income inequality. Higher education may exacerbate economic disparities due to the increased financial resources and developed capabilities of certain social classes.

Using yearly time series data from 1973 to 2012, this study explores the impact of the development of the higher education sector on income inequality in Pakistan. (Qazi et al., 2016). The cointegration technique of autoregressive distributed lag-bound testing verifies the existence of a long-term link between higher education and income inequality. The findings show that while there is a short-term negative but insignificant between higher education on income inequality, there is a long-term negative and substantial association between the two. The residuals of the income inequality equation do not appear to exhibit structural instability, according to the results of the cumulative sum (CUSUM) and square test CUSUM. The findings of causality studies validate the one-way causal link that exists in Pakistan between the growth of higher education and economic disparity, with the latter driving the former. The results of this analysis indicate that improving the distribution of income in Pakistan through

development in the higher education sector would be an important policy option to decrease income inequality.

2.1.3 Globalization

According to Dorn et al. (2018), this paper reexamines the relationship between income inequality and globalization. The data for chosen 140 nations are taken from 1970 to 2014. The relationship between globalization and income inequality depends on different nations. In the transitional nations, such as China and the majority of the Middle and Eastern European countries, there is a strong positive correlation between globalization and income inequality. Neither the OLS nor the 2SLS indicate a substantial positive link between globalization and inequality in the sample of the most developed economies. However, there is a strong positive relationship and significance between globalization and income inequality in transitional nations like China and the majority of Middle Eastern and Asian nations. Therefore, as countries become more integrated into the global economy, income inequality tends to increase. The observed systematic structural and institutional transformations towards market economies in transition nations from Central and Eastern Europe may be the unnoticed factors contributing to the increased levels of globalization and inequality shown in our findings.

This research examines at the effects of trade, finance, and technology globalization on income inequality in Asian rising nations, looking at each form of globalization independently (Munir & Bukhari, 2019). The study's theoretical framework for analyzing the connection between globalization and income inequality makes use of the Hecksher–Ohlin and Stolper–Samuelson theorems. The study used the instrumental variable least square (IVLS) and pooling least square (POLS) estimation techniques; however, due to endogeneity and biased omitted variable issues, IVLS is preferred over POLS. The study uses 11 countries (Bangladesh, China, India, Indonesia, Malaysia, Pakistan, Philippines, Sri Lanka, Singapore, South Korea, and Thailand) from 1980 to 2014 for the trade and technological globalization model and from 1990 to 2014 for the

financial globalization model due to the unavailability of data for all Asian emerging economies. Globalization of trade has a major impact on lowering income disparity in rising Asian nations. According to the way financial globalization affects income disparity, financial integration raises income inequality. As a result, the affluent and the poor do not gain equally from financial globalization. Globalization's impact on technology has a major positive influence on the decline in income disparity.

The current study aims to examine the connections between globalization and income inequality as well as between income disparity and economic growth (Abakumova & Primierova, 2018). From 1995 to 2016, the study used a single-country regression to examine whether the Kuznets curve hypothesis is suitable applied to the economy of Ukraine. The long-run connection between the variables is examined using the boundaries testing (ARDL) technique to cointegration. The findings validate the existence of hidden cointegration when the GDP per capita and the Gini index are regressed based on purchasing power parity. The Granger causality test used in this study. Granger causality was validated in the example of Ukraine, where the results indicate a positive correlation between globalization and economic disparity.

In emerging economies, this study empirically investigates the combined impact of globalization and financial growth on income inequality (Sethi et al., 2021). According to annual data on the Indian economy from 1980 to 2014, the apparent advantages of financial growth and globalization have not improved living standards, but have exacerbated income gaps. The findings also show that education appears to moderate the disparity effect, but inflation makes income disparities worse. To offset the adverse effects of globalization and financial growth on economic inequality, it is necessary to take proactive measures to provide financial services, establish equitable employment opportunities and improve the quality of education.

This study explores how globalization affects income inequality and social inequality in G10 countries (Zhu & Niu, 2024). Using yearly data from 1990 to 2021, cross-sectional auto-regressive distributed lagged models have been used. The long-term

results show that although technology advancements increase social inequality, globalization reduces income disparity. The short-term results demonstrate that globalization and technical innovation have a positive or negative relationship with income disparity.

According to Lee et al. (2019), this research investigates the effects of globalization on income inequality for a more extensive dataset of 121 countries from 1984 to 2014, guided by judgments of globalization in its broadest meaning. Nevertheless, the effects of globalization become insignificant or even detrimental when they are dependent on several sub-indices of political risk.

2.1.4 Corruption

According to Keneck-Massil et al. (2021), this study examines the connections between political power distribution, income inequality, and corruption across social classes in 172 developed and developing nations between 1975 and 2017. With the panel threshold effect model, the authors investigate nonlinearities, deal with weak time-variance, deal with endogeneity issues, and use a new sequential panel data estimator. Regardless of the form of corruption, the study reveals that low levels of corruption are linked to a decline in income disparity globally. Recall that corruption indices vary from the least democratic to the most democratic nations, therefore a rise denotes a lower amount of corruption.

This study examines the relationship between corruption and income disparity in Asian nations because Asian nations often have high rates of corruption and bad administration (Dwiputri, Arsyad, & Pradiptyo, 2018). The sample of Asian nations is reduced due to missing data on the independent and dependent variables. There were 56 samples of the research's sample data that satisfied the criteria to be examined. It is evident from the literature study that economic disparity and corruption are closely associated. Studies have repeatedly demonstrated that corruption may have a negative impact on economic growth and can increase income inequality. The research that

employs OLS, Tobit, and 2SLS regression techniques further validates the importance of the relationship between corruption and income disparity in Asia. In fact, some studies conclude that income inequality and corruption have a mutually reinforcing effect that might result in a corruption-inequality trap.

Ullah and Ahmad (2016) investigates the empirical link between corruption and income distribution using panel data on the corruption index, the Gini index of income inequality, and many state factors for 71 developed and developing nations. The research use Generalized Method of Moments (GMM) estimate technique, demonstrates that corruption plays a substantial role in the uneven distribution of wealth. This conclusion holds up well when considering various econometric connection parameters. One key finding about the link between corruption and income disparity is that it has a significant relationship on distribution and negative relationship between corruption and income inequality.

According to this study report, perceived unjust economic disparity may lead to corruption as a reaction (Policardo et al., 2019). Several investigations examining 34 OECD nations between 1995 and 2011 indicate that the relationship between corruption and income inequality varies by nation. Furthermore, income inequality has a beneficial impact on corruption, and corruption itself enhances income inequality.

By utilizing an imbalanced panel data set covering 48 countries in Sub-Saharan Africa between 1996 and 2016, empirical evidence added to the existing research (Sulemana & Kpienbaareh, 2018). The findings indicate that, in contrast to earlier findings from industrialized nations, higher levels of income inequality are linked to lower levels of corruption. This suggests that the connection between income inequality and corruption may be shifting among nations on various development trajectories. Additionally, corruption is a Granger-cause of wealth disparity and that there is a reverse causal relationship between the two. In conclusion, for low-income and lower-middle-income African nations, the findings of OLS, random effects, and fixed effects models show a

U-shaped association between corruption and income inequality, with turning point income inequality levels ranging from 22 to 52.

Examining a panel of fifty nations between 1995 and 2015, the causal relationship between corruption and income inequality varies depending on the nation and may even be bidirectional (Policardo & Carrera, 2018). According to a dynamic GMM model, corruption has a positive relationship with income inequality, but income inequality is not significantly influenced by corruption. Nonetheless, the significance of the test associated with the direction of causality, "corruption causes inequality," is smaller than the one associated with the relation, "income inequality causes corruption," leading the authors to believe that the number of countries for which corruption causes income inequality is smaller than the number of countries for which inequality causes corruption.

2.1.5 Foreign Direct Investment

According to Munir & Bukhari (2019), the purpose of the study is to investigate how income inequality and trade, finance, and technology globalization are related in a few Asian countries. Panel data from 1980 to 2014 is used for the trade and technology globalization model, while panel data from 1990 to 2014 is used for the financial globalization model. Instrumental variable least square and pooled ordinary least squares (OLS) are the estimate methods used in the analysis. In all three globalization models, foreign direct investment (FDI) acts as a control variable. The results show that trade and foreign direct investment have a considerable and favorable effect on income inequality. Not only that, FDI is predicted to have a positive relationship and significance on income inequality. It means that higher-skilled industries gain the most from FDI, which increases the demand and income of high-skilled workers. As a result, the study discovered that FDI will sharpen income inequality as FDI increases in the chosen Asian economies.

The purpose of this study is to examine the impact of inward foreign direct investment on income distribution in five South Asian countries between 1990 and 2016 (Khan et al., 2021). The analysis takes into account the potential non-linear effects of foreign direct investment on income distribution. The problem and endogeneity issues are reduced and solved by using the dynamic panel system generalized method of moments (SYS-GMM) estimator. The study concludes that FDI has a significant and positive relationship affect income inequality in selected South Asian countries.

According to Lê et al. (2021), this paper studies the impact of foreign direct investment on income inequality in Vietnam. This study uses Vietnamese provincial panel data which includes 63 provinces from 2012 to 2018. The purpose of the study is to examine how foreign direct investment affects income inequality, taking into account institutional and educational constraints. This paper uses a generalized method of moments (GMM) model for estimation to address potential endogeneity issues. This study utilizes a two-step GMM model with robust standard errors. Empirical results confirm the non-linear relationship between FDI and income inequality and show that FDI tends to increase income disparity in Vietnam. Furthermore, research shows that the impact of foreign direct investment (FDI) on income inequality varies depending on the educational attainment and institutional of the Vietnam.

This research examines the effects and interactions of foreign direct investment (FDI) inflows with income inequality in 36 Asian nations between 2000 and 2018 (Huynh, 2021). The findings show that FDI inflows worsen income inequality through two-step System Generalized Method of Moments (SGMM) and Feasible Generalized Least Squares (FGLS) estimation techniques . To solve autocorrelation and heteroscedasticity between panels, feasible generalized least squares (FGLS) used to fixed. For the two-step System Generalized Method of Moments (SGMM), it is a method used to estimate the technique to solve endogeneity concerns.

According to Soto et al. (2023), the study uses a panel data analysis in 46 low-tax countries during 2000 to 2021 to examine the impact of foreign direct investment (FDI) on income inequality in terms of several metrics. The findings show that FDI improves wellbeing and decrease income inequality in the nations after the study. When there is a favorable tax environment which is another variable, the findings will be more obvious.

Since the transition, there has been significant growth in both international trade and foreign direct investment (FDI). The goal of this article is to determine FDI is a major factor in explaining the pattern of income disparity in a subset of transition countries (Alili & Adnett, 2018). The findings show that although overall impact is less but increasing inbound FDI as a percentage of GDP increased income inequality in transition economies. Long-term data does not support a concave relationship between FDI and income inequality, which may be because many transition nations have very modest FDI levels.

In this research, 543 empirical research from 1995 to 2019 were used to do a meta-analysis on the impact of foreign direct investment (FDI) on inequality (Huang et al., 2020). The research nation's degree of development has the most impact on how FDI influences income inequality among other variables. The within-group estimates of the influence of foreign direct investment (FDI) on income inequality become very consistent with each other when the primary studies are divided into three groups according to the GDP per capita of their sample areas. FDI has a statistically significant on inequality for the middle-class group but is not significant for the high-income group. According to this finding, foreign direct investment (FDI) may contribute to income inequality when a country first belongs to a developing country but may also decrease when it develops.

2.1.6 Gross Domestic Product per capita

According to Akpa et al. (2024), this study investigates financial development in Sub-Saharan Africa (SSA) direct and indirect transmission mechanisms impact income inequality between years 1995 to 2015. The System Generalized Method of Moments (SGMM) was used to analyze the data. The results indicate that financial development will increase income inequality but when interacting with GDP per capita has a significant and negative relationship with income inequality. These findings suggest that financial development needs good economic growth to reduce income inequality.

This study examines the moderating effect of an aging population on financial inclusion and income inequality in 73 developing nations between 2004 and 2019 (Jamil et al., 2024). There is a significant relationship between financial inclusion on income inequality in selected developing nations. At low quantile levels, financial inclusion and an aging population influence the reduction of income inequality, based on the empirical results of a panel quantile regression. Therefore, GDP per capita has negative and significant relationship on income inequality. Due to the negative relationship between GDP per capita and income inequality, therefore income equality in developing countries when GDP per capita increases.

Through the years 1990 to 2015, this research attempts to investigate the causal linkages between economic growth, financial development, and income inequality in the BRICS (Brazil, Russia, India, China, and South Africa) countries (Younsi & Bechtini, 2018). The empirical results confirm Kuznets' inverted U-shaped theory regarding the relationship between economic growth and income inequality. Income disparity is positively and statistically significantly impacted by GDP per capita. Furthermore, Kuznets' inverted U-shaped link between financial development and income disparity is supported by the data.

According to Chang et al. (2016), this study examines the link between six indicators of income inequality and the real GDP per capita in the United States from 1917 to 2012 using wavelet coherency analysis. The simultaneous investigation of the two series' causation and correlation in the time and frequency domains is made possible by wavelet analysis. Strong evidence of a positive association between inequality and growth across frequencies is presented by our data. However, causation directions change over time and across frequency. For the Top 1 and 10% measures of inequality, there is evidence that inequality leads real GDP per capita at both high and low frequencies, but there is minimal evidence that real GDP per capita leads inequality. Therefore, it shows a not significant between real GDP per capita and income inequality. The time-varying nature of long-run causalities suggests that the two series' structural characteristics have changed in the temporal domain.

2.1.7 Unemployment rate

According to Deyshappriya (2017), this study uses dynamic panel data analysis to investigate the macroeconomic factors that influence income inequality. The study specifically uses dynamic panel data analysis spanning the years from 1990 to 2013 across 33 Asian nations, based on the generalized method of moments (GMM). The World Bank data series served as a popular source of information for macroeconomic indicators, while the World Income Inequality Database provided the Gini index. To provide more accurate estimations, the research takes into account a number of political, economic, and demographic variables in addition to the macroeconomic ones. Aside from that, there is a strong correlation between income disparity and unemployment, and rising rates of unemployment will intensify inequality in Asian nations.

According to Shabnum and Malik (2023), this study uses several methods to evaluate the extent of income inequality in Pakistan. Using a logit model with data from 1980 to 2020, it determines the effect of macroeconomic variables on the level of income inequality, such as unemployment. The Gini Index indicates that Pakistan's metropolitan areas have higher rates of income disparity than the country's rural parts. On the other hand, Punjab is the province most negatively impacted by the unequal

distribution of income. The relevance of each chosen variable about income inequality in Pakistan is demonstrated by the regression findings. It demonstrates that the Gini index is negatively impacted by unemployment.

2.2 Review of Relevant Theoretical Models

2.2.1 Lorenz Curve

An illustration of the distribution of wealth or income within a population is called a Lorenz curve (I. Team, 2022). The population's percentiles are plotted against the total wealth or income of those who fall inside that percentile on Lorenz curves. The basic approach is demonstrated using data from the United Nations University-World Income disparity Database, which includes the Gini index and the income shares of four nations with varying degrees of income disparity as well as economic, sociological, and geographical backgrounds (Sitthiyot & Holasut, 2021). Overall, the findings show that the predicted Lorenz curves provided a nearly perfect match to the real observations. When information on income distribution is scarce, this straightforward approach may be helpful. This study indicates that the Lorenz curve might be directly estimated using the designated functional form in the event that more income distribution data become available. Furthermore, the estimated values of the Gini index that are computed using the given functional form are almost exactly the same as their real data.

2.2.2 Kuznets' inverted-U hypothesis

Simon Kuznets postulated in the 1950s that there is an inverse U-shaped link between development and inequality (Rehal & Rehal, 2024). Based on the Kuznets Curve, at the early stage of economic development, income inequality would increase with the level of income until a certain level of GDP per capita is reached which is turning

point (Le et al., 2020). When reached, development of industrialization, globalization, and welfare will help to reduce income inequality. In this process, corruption, education and foreign direct investment are important factors. Early on, inequality is made worse by a lack of educational opportunities, and globalization may make things worse by favoring some groups of people over others. Allocating resources is further distorted by corruption. But when countries develop, more money is spent on education, which lowers inequality by offering more equal options. With the right rules in place, globalization may boost production and benefit all societal classes. Furthermore, more equitable resource allocation is promoted by fortifying institutions to fight corruption. As nations move along the Kuznets Curve, these variables may therefore initially contribute to inequality but also ease its reduction, highlighting the need of good policies in promoting fair development (Rahman & Alam, 2022).

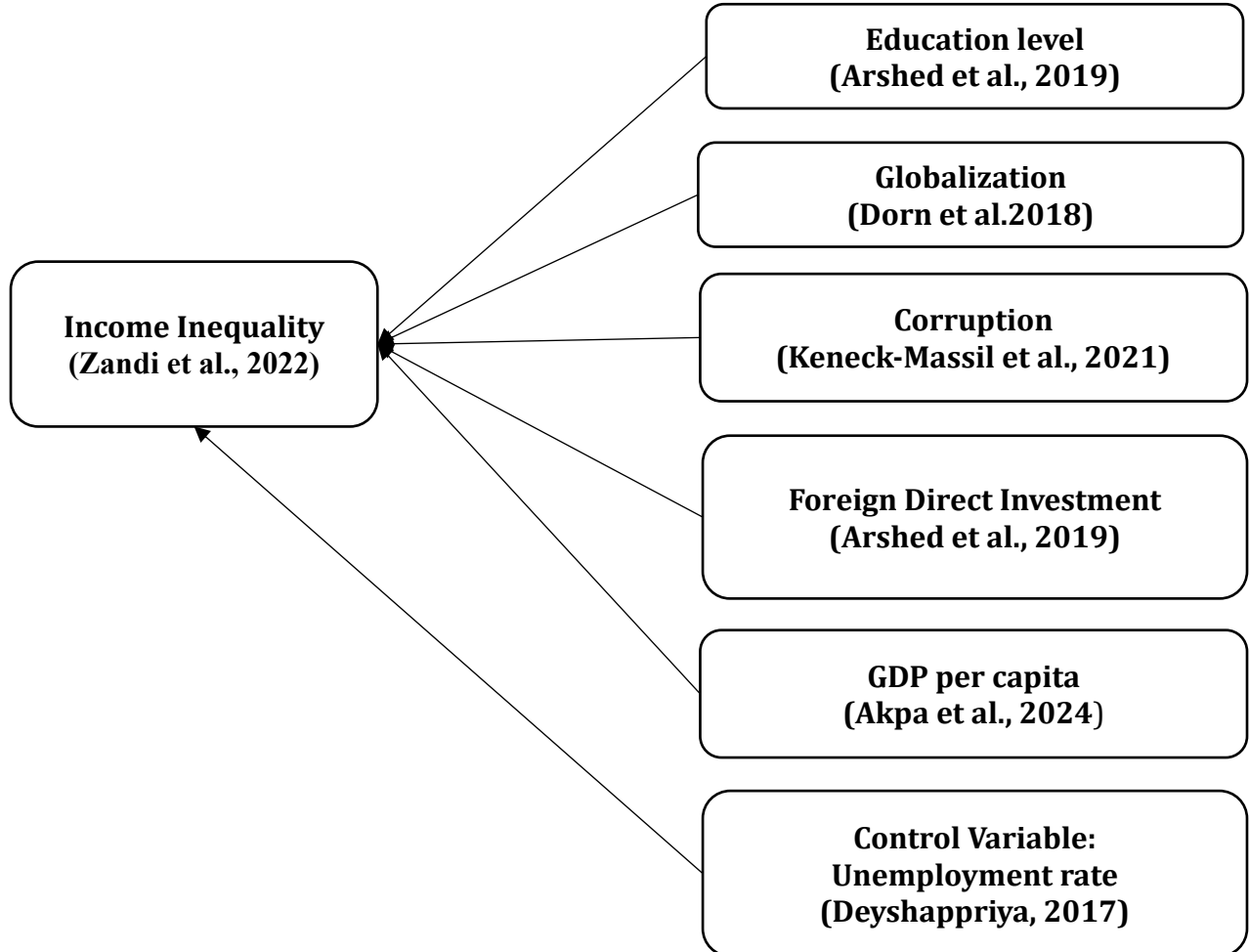
2.2.3 Human Capital Theory

Human capital refers to an employee's educational background, expertise, experience, and talents (Ross, 2023). It claims that businesses are compelled to look for and develop the human capital of their current workforce. Stated differently, the idea of human capital acknowledges that labour capital is not a monolithic entity. Economists Theodore Schultz and Gary Becker noted in the 1960s that investing in education and training may increase productivity (Ross, 2023).

The unequal distribution of income among people or households within a society is referred to as income inequality. The correlation between income disparity and education level is well-established. People who have completed more schooling often have greater incomes, while others who have not completed as much education usually have lower incomes. Income inequality in a society is exacerbated by the disparity in income between education levels (Park, 2017).

2.3 Conceptual Framework

Figure 2.1: Conceptual Framework



Source: Developed from the research

The conceptual framework in Figure 1 shows that 5 independent variables which are education level, globalization, corruption, foreign direct investment, GDP per capita and control variable is unemployment rate had been chosen to examine the relationship between the dependent variable, income inequality.

2.4 Model Specification

$$GINI_{it} = \beta_0 + \beta_1 EL_{it} + \beta_2 GL_{it} + \beta_3 CC_{it} + \beta_4 \ln FDI_{it} + \beta_5 \ln GDP_{it} + \beta_6 UN + \alpha_i + \mu_{it}$$

Where: *GINI* = Gini coefficient (index point)
EL = School enrollment, tertiary (Gross %)
GL = KOF Globalization Index (%)
CC = Corruption Perceptions Index (%)
lnFDI = Foreign Direct Investment (real US\$)
lnGDP = Gross Domestic Product per Capita (real US\$)
UN = Gross Domestic Product per Capita (real US\$)
T = time trend 2015 to 2020 yearly data
 α = unidentified intercept
 μ = error term
it = cross sectional and time series data

2.5 Research Gap

This study aims to fill this gap in the literature and offers an analysis which critically examines the relationship between education level, corruption, globalization, FDI inflows and GDP per capita for a panel data set of 33 developing countries using the yearly data from 2015 to 2020.

This study used the up-to-date data collected from official sources. The timeliness of data is crucial to the reliability and quality of research results in the field of economics. As new data are released, people will be able to understand the impact of existing education levels, globalization, corruption, foreign direct investment and GDP per capita on income inequality. Additionally, any modifications, patterns, or

conclusions that can be drawn from the existing data can be used to update strategies for addressing income inequality.

2.6 Conclusion

In conclusion, chapter 2 has provided a comprehensive review of the literature on factors affecting income inequality such as education level, globalization, corruption, foreign direct investment, gross domestic product per capita and unemployment rate. These previous studies have highlighted the relationship such as significant, insignificant, positive or negative relationship between income inequality and independent variables in developing countries.

Chapter 3: Methodology

3.0 Introduction

The five main elements of research methodology are research design, data collection method, research instrument, data processing, and model estimation.

3.1 Research Design

Gathering and evaluating numerical data is the process of doing quantitative research to have a better understanding of events, connections, and trends within a population. Regarding the study design, it incorporates aspects of both causal and descriptive research. In this instance, the data that is currently available may be used to characterize the tertiary enrollment of education, globalization indexes, views of corruption, foreign direct investment, gross domestic product per capita and income inequality across different developing nations. These qualities would be compiled and presented using descriptive statistics. Finding causality, or the cause-and-effect link between variables, is the goal of causal research. This would include assessing statistical correlations and

maybe using methods like regression analysis to determine how much changes in globalization, corruption, educational attainment, foreign direct investment, and gross domestic product per capita impact income inequality. The dependent variable, independent variables and control variables are listed as below:

Table 3.1: List of variables used in the study

Abbreviation	Variable	Unit
Dependent Variables		
GINI	GINI coefficient	Index point
Independent Variables		
EL	School enrollment, tertiary	%
GL	KOF Globalization Index	%
CC	Corruption Perceptions Index	%
FDI	Foreign Direct Investment	Real USD
GDP	GDP per capita	Real USD
Control Variables		
UR	Unemployment rate	%

3.2 Data Collection Method

In this research, the panel data consists of yearly secondary data that is obtained from World Development Indicators, KOF Swiss Economic Institute and Transparency International with the time period of 6 years, spanning from 2015 to 2020, for 33 countries. Besides, the panel data set is considered unbalanced.

Table 3.2: Selected developing countries

Country	
Albania	Argentina

Armenia	Belarus
Bulgaria	Brazil
Chile	Colombia
Costa Rica	Dominican Republic
Ecuador	Egypt
El Salvador	Georgia
Hungary	India
Indonesia	Kazakhstan
Kyrgyz Republic	Mexico
Montenegro	Moldova
North Macedonia	Panama
Poland	Romania
Russian Federation	Serbia
Thailand	Turkiye
Ukraine	Uruguay
Vietnam	

3.2.1 Definition of variables

Income Inequality (GINI)

Income inequality, measured by Gini index. The degree to which income is distributed unequally among a population is referred to as income inequality (The World Bank, 2023). For example, inequality of income, which refers to the distribution of wealth across households or individuals at a particular point in time, and inequality of opportunity, which refers to the impact on income of circumstances over which individuals have no control, such as family socioeconomic status, gender, or ethnic background, are related concepts.

A common way to quantify income disparity is the Gini coefficient. It ranges from 0 to 1, with 0 denoting perfect equality and 1 denoting complete inequality. The idea of income inequality as defined by the Gini coefficient, which is accessible for a wide number of nations and relatively lengthy periods, is the focus of the majority of the analysis. Gini income inequality, unless otherwise stated, relates to disposable income or consumption and so already accounts for any redistribution made by taxes and transfers.

School enrollment, tertiary (% gross) (EL)

The ratio of all enrolled people, regardless of age, to the population in the age group that officially corresponds to the shown level of education is known as the gross enrollment ratio. A secondary education must typically be completed successfully to be admitted to tertiary education, whether or not to an advanced research diploma.

KOF Globalization Index (GL)

The economic, social, and political dimensions of globalization are measured by the KOF Globalization Index. Since the conclusion of the Cold War, there has been an increase in globalization in several disciplines, which began in the 1970s. A score of zero denotes low levels of globalization, while a score of 100 denotes highest levels.

Corruption Perceptions Index (CC)

According to Kenton (2021), the Corruption Perceptions Index (CPI) is a rating system that assigns a number to each nation based on how corrupt their governments are thought to be. A score of zero denotes high levels of corruption, while a score of 100 denotes low levels. Transparency International, a group dedicated to combating bribery, fraud, and other types of corruption in the public sector, releases the CPI each year.

Foreign Direct Investment (FDI)

The net inflows of capital intended to obtain a long-term management stake (10 percent or more of voting shares) in a business that operates in a different economy than the investors are known as foreign direct investment. As shown by the balance of payments, it is the total of equity capital, earnings reinvested, other long-term capital, and short-term capital. This data, which is split by GDP, displays net inflows (new investment inflows less disinvestment) from foreign investors into the reporting economy.

Gross Domestic Product per capita (GDP per capita)

The gross domestic product divided by the population at midyear yields GDP per capita. GDP is the total of the gross value contributed by all producers who are residents of the country, plus any product taxes and minus any subsidies that aren't factored into the product value. It is computed without accounting for the depletion and deterioration of natural resources or the depreciation of artificial assets. Current U.S. dollars are used for data.

Unemployment rate (UN)

Unemployment is the proportion of the labor force that is unemployed but still actively seeking for job.

3.3 Research Instrument

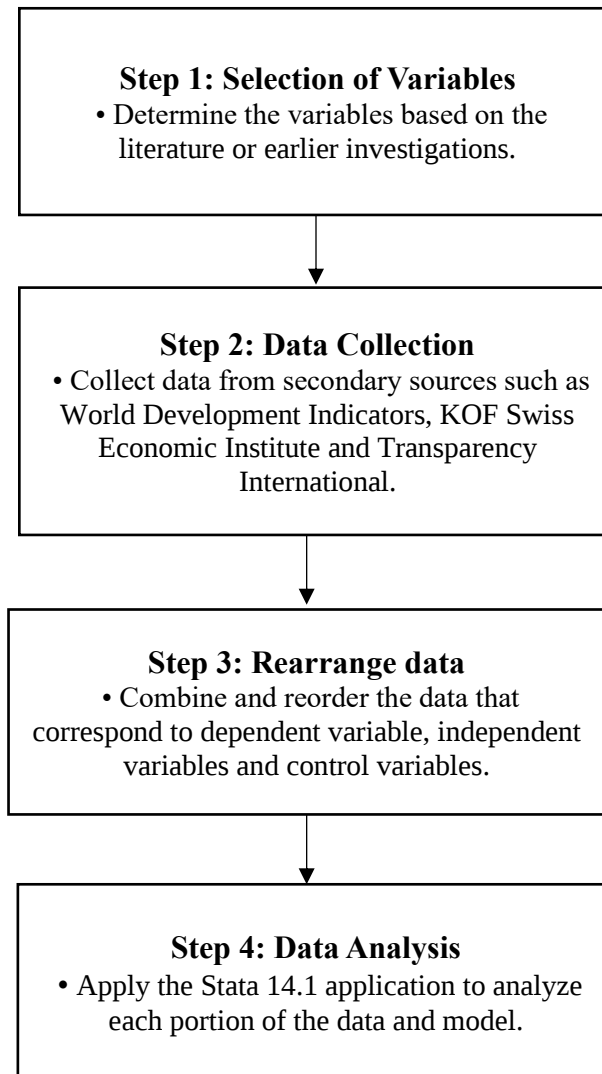
Stata 14.1 is a tool used in many academic fields primarily for managing and analyzing data. Stata's extensive command set makes it easy to perform statistical tests, explore large data sets, and create informative visualizations. Stata provides the tools you need to effectively perform a variety of statistical procedures, including survey data analysis, regression analysis, and complex econometric modeling. It can handle a wide range of data types and complex study designs, demonstrating its adaptability. Stata 14.1 is a

reliable tool for researchers due to its regular upgrades and support for reproducible research procedures and its ability to accurately statistically analyze data.

3.4 Data Processing

For data processing, 5 independent variables will affect income inequality in 33 developing countries. The data are taken from 2015 to 2020. The variables are education level, globalization, corruption, foreign direct investment, and GDP per capita. Moreover, the unemployment rate is the control variable in the research. From Figure 3.1, the data processing flow is shown below.

Figure 3.1 Data Processing Flows





Step 5: Interpretation of results

- Interpret the result get from Stata 14.1.

3.5 Model Estimation

The primary data analysis tool in this research paper is Stata 14.1. A variety of panel data analysis techniques are used, such as Pooled Ordinary Least Squares (POLS), fixed effect model (FEM), random effect model (REM), Hausman test, diagnostic tests, Breusch and Pagan Lagrange Multiplier test (BP LM test), and Panel Corrected Standard Error (PCSE) model. These techniques are used to analyze relationships across panel datasets, evaluate model specifications, and identify possible problems like heteroscedasticity, autocorrelation and multicollinearity.

3.5.1 Static Panel Analytic Model

3.5.1.1 Pooled Ordinary Least Square (POLS)

The panel format of the data is ignored by the Pooled Ordinary Least Squares (OLS) regression model, also known as the common constant model, which assumes constant intercepts and slopes for both individual units and time periods. As a result, data pooling is possible, making OLS regression analysis possible (Hiestand, 2005). This method uses OLS to aggregate the squared residuals over all observations in the sample dataset, and then select estimators for the slope (β_1) and intercept (β_0) parameters. An example of POLS equation is illustrated as below:

$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i \quad (1)$$

Where: $Y_i = \text{dependent variable}$
 $X_i = \text{independent variable}$
 $\beta_0 = \text{constant intercept}$
 $\beta_1 = \text{constant slopes}$
 $\varepsilon_{it} = \text{stochastic error term}$

To get the coefficient of β_0 and β_1 , the following is the formula:

$$\beta_1 = \frac{\sum(X - \bar{X})(Y - \bar{Y})}{\sum(X - \bar{X})^2} \quad (2)$$

With β_1 calculated:

$$\beta_0 = \bar{Y} - \beta_1 \bar{X}_i \quad (3)$$

Where: $\bar{X} = \text{mean of } X$
 $\bar{Y} = \text{mean of } Y$

Pooled Ordinary Least Squares (POLS) is the estimate model has the benefit of being more straightforward than other econometric methods. Since POLS requires little computing complexity and does not rely on computers or calculators for estimate, it's frequently considered the simplest approach to employ (Studenmund, 2014). Furthermore, POLS is deemed to provide estimators that are "BLUE" (Best Linear

Unbiased Estimators) based on classical assumptions, which adds to its allure. Building on the basis of POLS, several alternative estimating approaches use iterative processes or more intricate non-linear formulae. Because POLS is based on reducing squared residuals, it closely approximates observed data, which improves the estimation model's accuracy. This framework is in line with theoretical ideas.

3.5.1.2 Fixed Effect Model (FEM)

A static estimating method called the Fixed Effect Model (FEM) is used to examine how a variable that changes over time within a nation affects results. Under FEM, the dependent variable varies in reaction to changes in the independent factors, while the levels of the independent variables are assumed to remain constant. It asserts that every nation has particular qualities that lead to different error terms and constants for every nation, which ought not to be compared with those of other nations (Torres-Reyna, 2007). When evaluating data, FEM efficiently eliminates the impacts of time-invariant features, enabling a more accurate assessment of the net influence of independent factors on the dependent variable within each nation. The FEM equation will be illustrated as bellow:

$$Y_{it} = \beta_0 + \beta_1 X_{it} + \lambda_i + \mu_{it} \quad (4)$$

Where:

Y_{it} = dependent variable

X_{it} = independent variable

β_0 = constant intercept

β_1 = coefficient of the independent variable

λ_i = individual – specific effect

μ_{it} = error term

it = country and time respectively

3.5.1.3 Random Effect Model (REM)

Country-specific differences are assumed to be random and unrelated to the dependent and independent variables used in the Random Effects Model (REM). When it is anticipated that cross-national variations would have an impact on the dependent variable, this strategy is highly suitable. In REM, time-invariant variables serve as explanatory variables since it is assumed that the error term associated with each country is uncorrelated with the independent variables. These concepts are encapsulated in the REM equation, which, by accounting for both apparent and unobserved heterogeneity, enables a comprehensive analysis of cross-country data. The equation of REM is shown below:

$$\varepsilon_{it} = \lambda_i + \mu_{it} \quad (9)$$

Where: λ_i = individual effect which REM assumes it to be random

μ_{it} = the remainder error term

Original equation:

$$Y_{it} = \beta_1 X_{it} + \varepsilon_{it} \quad (10)$$

Substitute with equation (9):

$$Y_{it} = \beta_1 X_{it} + \lambda_i + \mu_{it} \quad (11)$$

Gurka, Kelley, and Edwards (2011) have shown that the accuracy of data representation is enhanced when the Random Effects Model (REM) is used in complex study designs including multilevel and longitudinal studies. Law (2018) states that REM is particularly useful for datasets that are resilient to serial correlation and comprise randomly selected countries from a large pool. Additionally, the efficacy and consistency of REM have been emphasized, especially in cases where the explanatory factors and the unit-specific impact are unrelated. The Generalized Least Squares (GLS) estimator provides a solid basis for analyzing such data structures and is the suggested estimate for REM. The equation of GLS is illustrated as:

$$(Y_{it} - \theta \bar{Y}_t) = \beta_0 + \beta_1(X_{it} - \theta \bar{X}_t) \quad (12)$$

$$\text{Where } \theta = 1 - \frac{\sigma_u^2}{\sigma_\lambda^2 + \sigma_u^2} \quad (13)$$

Note: σ_u^2 = variance of error term

σ_λ^2 = variance of individual-special effect

3.5.2 Static Panel Models Selection

Breusch and Pagan Lagrange Multiplier Tests as well as Hausman Tests are used to identify which panel model among POLS, FEM, and REM is most suited for the investigation.

3.5.2.1 Breusch and Pagan Lagrange Multiplier Test (BP LM Test)

The BP LM Test is a phase in the model evaluation process that determines which of the two models, POLS or REM, is better suited for usage in this investigation. For this BP LM Test, the following hypothesis is developed:

Hypothesis: H_0 = *Pooled OLS (POLS) specification is to be preferred*

H_1 = *Random effects (REM) specification is to be preferred*

The null hypothesis (H_0) will be rejected if the p-value from the BP LM test is less than the 5% significance level. In this scenario, the Ordinary Least Squares (POLS) model is judged less appropriate for this investigation than the Random Effects model (REM). In contrast, the null hypothesis cannot be rejected if the p-value is greater than the 5% significance level, suggesting that the POLS model is more preferred for the data.

3.5.2.2 Hausman Test

After removing POLS through the BP LM test and determining random effect to be more favorable, the Hausman Test should be executed to assess heterogeneity, aiming to discern which model, REM or FEM, exhibits superior accuracy. The Hausman Test hypothesis is formulated as follows:

Hypothesis: $H_0 = \text{Random effects (REM) specification is to be preferred}$
 $H_1 = \text{Fixed effects (FEM) specification is to be preferred}$

It is implied that there is correlation between the independent variable (X_{it}) and individual effect (λ_i) if the p-value is smaller than the significant threshold at 5%. As a result, fixed effect is more suited and H_0 will be rejected. Random effect is favored than fixed effect, yet, if the p-value is greater than the significant level at 5%, H_0 will not be rejected.

3.5.3 Diagnostic Test for Static Panel Analytic Model

3.5.3.1 Heteroscedasticity

Regressions that exhibit heteroscedasticity deviate from the traditional assumption V (Studenmund, 2014), which states that regression should ideally have homoscedasticity and constant error terms (Williams, 2015). Recognizing this residual issue in regression entails noting that mistakes grow with an increase in the independent variable (IV).

The presence of heteroscedasticity in regression undermines the foundation of parameter estimation, while also diminishing the accuracy of predicting standard errors for coefficients. Moreover, the variance of results ceases to be minimal, resulting in unreliable relationships between test statistics and confidence intervals. Consequently, hypothesis testing becomes less reliable. Detecting this residual issue in regression

involves employing the Wald test in this study. The hypotheses for heteroscedasticity testing are as follows:

Hypothesis: $H_0 = \text{Residuals are homoscedastic}$

$H_1 = \text{Residuals are heteroscedastic}$

3.5.3.2 Serial Correlation

When serial correlation is found in the regression, traditional assumption IV is broken. The observations of the error term are correlated when pure serial correlation takes place. In particular, the diagnosis of first-order serial correlation implies that the variable's previous experiences have an impact on its current value. The strength of serial correlation is determined by the value of ρ , which has a range of -1 to +1.

$$-1 < \rho < +1 \quad (14)$$

The error term seems to show no serial correlation when the ρ is equal to 0; otherwise, it shows serial correlation. The strongest autocorrelation, or serial correlation, occurs as the coefficient ρ becomes closer to an absolute value of 1. According to Studenmund (2014), a positive ρ value indicates that the error terms remain positive throughout, whereas a negative ρ indicates fluctuation between positive and negative signals during observations. Models utilizing Random Effects Model (REM) in panel analysis need not undergo serial correlation testing as the estimators derived from REM inherently address this issue (Law, 2018). Like heteroscedasticity, autocorrelation has no biasing effects on coefficient estimations when it comes to regression effects. However, because the variance estimator is no longer minimum, Ordinary Least Squares (OLS) estimators become biased and produce incorrect findings in hypothesis testing. The hypothesis for the serial correlation test are listed below:

Hypothesis: $H_0 = \text{Residuals are no serial correlation}$

$H_1 = \text{Residuals are serial correlation}$

3.5.3.3 Multicollinearity

Regression analysis's variance inflation factor (VIF) is a metric for multicollinearity. In a multivariate regression model, multicollinearity occurs when there is a correlation between several independent variables (Team, 2023). The regression findings may suffer as a result of this. As a result, the variance inflation factor may be used to calculate the extent to which multicollinearity has inflated the variance of a regression coefficient. Variables with a VIF of 1 indicate no correlation, those with a VIF of 1 to 5 indicate moderate correlation, and those with a VIF of higher than 5 indicate high correlation. More study is necessary the greater the VIF, which indicates a larger likelihood of multicollinearity. There is severe multicollinearity that needs to be adjusted when the VIF is more than 10.

3.5.4 Panel-corrected Standard Error (PCSE)

Panel Corrected Standard Errors are a popular technique for examining cross-sectional and time series data because they may yield accurate standard error estimates (Reed & Webb, 2010). Ordinary Least Squares are first used to estimate parameters (OLS). However, PCSE outperforms OLS to produce more accurate estimations because of OLS's intrinsic problems, which include heteroscedasticity and serial correlation within the residuals. By computing standard errors, PCSE directly addresses these lingering concerns and successfully mitigates previously encountered and acknowledged problems. The PCSE formulation designed especially for panel data is shown in the following equation.

The diagonal elements' square roots in the matrix will be produced as panel-corrected standard error:

$$\text{cov}(b) = (X'X)^{-1}(X'(\Phi \text{ I}_T)X)(X'X)^{-1} \quad (15)$$

where $\Phi = N \times N$ matrix with the $(i, j)^{th}$ element estimated by :

$$(\sum_{t=1}^T \hat{e}_{i,t} \hat{e}_{j,t})/T \quad (16)$$

3.6 Conclusion

This chapter followed the primary test outline from the previous chapter to give the test results based on the Stata. The study's summary, implications, limitations, and suggestions for further research will all be covered in Chapter 5.

Chapter 4: Data Analysis

4.0 Introduction

This chapter will discuss on the results obtained from descriptive analysis, model evaluations, research estimation methods, and residual diagnosis for factors affecting income inequality in developing countries.

4.1 Correlation Metrix

Table 4.1: Correlation Metrix of variables that used in model

	GINI	EL	CR	GL	IFDI	IGDP	UR
GINI	1.0000						
EL	-0.0465	1.0000					
CR	0.1252	0.1875	1.0000				
GL	-0.0721	0.3807	0.5949	1.0000			
IFDI	0.3744	0.0357	0.0306	0.0411	1.0000		
IGDP	0.3798	0.4374	0.4756	0.5133	0.2812	1.0000	
UR	0.1357	0.1058	0.1597	0.0048	-0.1990	-0.0357	1.0000

4.2 Results for Descriptive Analysis

Table 4.2: Descriptive Analysis of variables that used in model

Abbreviation	Variable	Mean	Std. Dev.	Min	Max	Observation
GINI	Income Inequality	37.396	7.599821	24.4	53.9	175
EL	Enrollment of tertiary school	58.45483	19.75822	26.17383	118.8837	185
CR	Corruption	40.57051	10.72274	27	74	198
GL	Globalization	69.44667	7.865677	53.53	86.86	198
IFDI	Logarithmic Foreign direct investment	22.03096	1.702768	15.85592	25.84482	189
IGDP	Logarithmic GDP per capita	8.784538	0.6393548	7.021679	9.853564	198
UR	Unemployment rate	7.907071	4.847962	0.6	26.43	198

Source: Own Data Collection via STATA

The captured data are used to perform the descriptive analysis. The central tendency in this analysis is represented by the mean, minimum, and maximum amounts. Aside from that, the analysis's variability is tested using the standard deviation. With 175 observations, the income inequality dataset has a mean of 37.396 and a range of 24.4 to 53.9. The 185 observations for tertiary education enrollment show a variety in

enrollment rates, with a mean of 58.45483 and a range from 26.17383 to 118.8837. Based on 198 observations, the mean value for corruption perception is 40.57051, with a range of 27 to 74, indicating a variation in corruption levels. Analysis of 198 data reveals a wide range of globalization levels, with a mean of 69.44667 and a range of 53.53 to 86.86.

Logarithmic FDI variance is explained by yielding a mean of 22.03096 with a range of 15.85592 to 25.84482, based on 189 observations of logarithmic FDI data. Based on 198 observations, the mean logarithmic GDP per capita is 8.784538, with a range of 7.021679 to 9.853564, illustrating the variability in economic wealth. Finally, statistics on unemployment rates, gathered from 198 observations, show that unemployment rates vary; the mean is 7.907071, and the range is 0.6 to 26.43. These datasets provide rich analytical foundations for a range of socioeconomic variables.

Table 4.3 The result of Estimated Model

Estimated Model				
Variables	(1) POLS	(2) REM	(3) FEM	Panel-Correct Standard Error (PCSE)
EL	-0.08037***	-0.0442	-0.05875*	-0.0804
	(0.0296)	(0.028)	(0.03004)	(0.06414)
CR	0.0357	-0.0273	-0.06051	0.03569
	(0.0619)	(0.0448)	(0.04661)	(0.105976)
GL	-0.2951***	-0.11116	-0.1398	-0.29515
	(0.08458)	(0.0837)	(0.09372)	(0.21872)
lFDI	1.2968***	0.4224**	0.28025	1.2968**
	(0.3124)	(0.21)	(0.21232)	(0.55436)
lgDP	6.5815***	0.9706	-0.59186	6.581481***
	(1.0824)	(0.9955)	(1.0401)	(1.84787)
UR	0.3658***	0.4173***	0.36191***	0.36583

	(0.11)	(0.0808)	(0.08484)	(0.10598)
Constant	-28.0835***	27.6980***	49.10549***	-28.08351
	(9.3861)	(10.567)	(12.8983)	(20.23026)
Number of Observation	155	155	155	155
Number of groups	-	33	33	33
R-squared	0.3789	0.2234	0.2453	0.3789
Breusch-Pagan LM test	234.52 (0.0000)***		-	-
Hausman test	-	31.73 (0.0000)***		-
Heteroskedasticity (x ² - stat)	-	-	2.6e+30 (0.0000)***	-
Serial Correlation (F- stat)	-	-	13.342 (0.0012)***	-

Source: Own Data Collection via STATA

Note: ***p<0.01, **p<0.05, *p<0.1

EL = education level

CC = corruption

GL= globalization

IFDI = foreign direct investment

IGDP = GDP per capita

UR = unemployment rate

Three different estimation methods are used to analyze the data. This study uses panel corrected standard error (PCSE), fixed effect models (FEM), random effect models (REM), and pooled ordinary least squares (POLS) to investigate and explain the impact of independent factors on dependent variables like the Gini coefficient-measured income inequality in developing nations. Breusch and Pagan's Lagrange Multiplier test and the Hausman test are used to assess which model is most appropriate for this study.

The FEM model is recommended, according to the findings of the Hausman test in Section 4.3 and the Breusch and Pagan Lagrange Multiplier test.

Based on the FEM results, EL and UR are significant which negative and positive relationship, whereas all other factors are not significant. Fixed Effect Models (FEM) appear to be the preferred option than POLS and REM based on the findings of the Hausman test and the Breusch and Pagan Lagrange Multiplier test. Moreover, Panel Corrected Standard Error (PCSE) is used after cluster heteroscedasticity and autocorrelation. The Panel Corrected Standard Error (PCSE) results of the estimated model show that income inequality in developing nations is increased by foreign direct investment. 1% increase in foreign direct investment (lFDI), on average, has a positive relationship impact on increasing income inequality by 1.2968% with statically significance at the level of 0.05, holding the other variables constant. The results demonstrate that lFDI is a statically significant result with a positive sign. This conclusion is in line with the body of research, which suggests that nations receiving greater foreign direct investment would increase in income disparity (Khan et al., 2021). Furthermore, the research indicates that the impact of foreign direct investment (FDI) on income inequality varies based on the educational attainment and institutional setup of the host countries. As a result, the findings indicated that there is a statistically significant correlation between rising FDI and rising income disparity. Additionally, foreign direct investment (FDI) may provide new job opportunities, but they would primarily be in low-wage industries, exacerbating the already existing wealth gap. This conclusion is in line with the body of research, which suggests that nations receiving higher levels of foreign direct investment would see an increase in income disparity (Younsi & Bechtini, 2018).

Furthermore, a 1% increase in gross domestic product per capita (lGDP) is associated with an average positive relationship effect that increases income inequality by 6.581481% with statically significant at the level of 0.01 while holding other variables constant. The empirical findings support Kuznets' idea of the inverted U-shaped link between income inequality and economic growth. GDP per capita has a statistically

significant and favorable influence on income disparities. Not only that, the significance of the test associated with the direction of causality, "corruption causes inequality," is smaller than the one associated with the relation, "income inequality causes corruption," leading the authors to believe that the number of countries for which corruption causes income inequality is smaller than the number of countries for which inequality causes corruption. Therefore, it shows a not significant relationship between corruption and income inequality.

Through the findings, EL, CR, GL and UR are all insignificant as their p-value are more than 0.01, 0.05 and 0.1. Therefore, educational level, corruption, globalization and the unemployment rate are not sensitive to income inequality in developing countries. Based on other previous research, corruption has a positive relationship with income inequality, but income inequality is not significantly influenced by corruption. Not only that, the significance of the test associated with the direction of causality, "corruption causes inequality," is smaller than the one associated with the relation, "income inequality causes corruption," leading the authors to believe that the number of countries for which corruption causes income inequality is smaller than the number of countries for which inequality causes corruption. Therefore, it shows a not significant relationship between corruption and income inequality.

4.3 Results for Model Evaluation

4.3.1 Breusch & Pagan LM Test (BP LM test)

Table 4.4.1(a): Hypothesis for Breusch & Pagan LM Test

Hypothesis: H_0 = Pooled OLS (POLS) specification is to be preferred

H_1 = Random effects (REM) specification is to be preferred

Table 4.4.1(b): Breusch & Pagan LM Test Analysis

Diagnostic Test	Result	Decision
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BP LM test: Chi square (Chi ²), Probability (P-value): < or > $\alpha=5\%$	Chi ² = 234.52 P-value = 0.0000	P-value < 5%, therefore, Reject H_0
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Source: Own Data Collection via STATA

In Model, 1 the p-value obtained from the BP LM test is identical. The p-value of model is 0.0000, which is less than 0.05 or significant level at 5%. Therefore, reject H_0 and Random Effect Model is more preferred to be used.

4.3.2 Hausman Fixed Test

Table 4.4.2(a): Hypothesis for Hausman Fixed Test

Hypothesis: H_0 = Random effects (REM) specification is to be preferred
 H_1 = Fixed effects (FEM) specification is to be preferred

Table 4.4.2(b): Hausman Fixed Test Analysis

Diagnostic Test	Result	Decision
Hausman fixed test: Chi square (Chi ²), Probability (P-value): < or > $\alpha=5\%$	Chi ² = 31.73 P- value = 0.0000	P-value < 5%, therefore, Reject H_0

Source: Own Data Collection via STATA

REM is shown to be more appropriate for the model than POLS based on the results of the BP LM test. The Hausman test is used to ascertain whether REM or FEM fits the better regressions. Due to p-value of Model 1 is 0.0000, which is less than the significant level at 5%, therefore, H_0 is rejected, and FEM is the better option for Model.

Following the Hausman Fixed test, the adequacy of the research strategy indicated by the Hausman Fixed test is verified using the heteroscedasticity test and serial

correlation test. The model has residual issues, as indicated in table 4.3.1(b) and 4.3.2(b). As a result, the static panel model in this study uses the Panel-Correct Standard Error (PCSE) technique, with the error terms being addressed to the residual difficulties.

4.4 Results for Diagnostic Test

4.4.1 Heteroscedasticity

Table 4.5.1 (a): Hypothesis for Heteroscedasticity Test

Hypothesis: $H_0 = \text{Residuals are homoscedastic}$

$H_1 = \text{Residuals are heteroscedastic}$

Table 4.5.1 (b): Heteroscedasticity Analysis

Diagnostic Test	Result	Decision
Heteroscedasticity test: Chi square (Chi ²), Probability (P-value): $> \alpha=5\%$	Chi ² = 2.6e+30 P-value = 0.0000	P- value < 5%, therefore, Reject H_0

Source: Own Data Collection via STATA

If the p-value is more than α (5%), the null hypothesis cannot be rejected. The p-value from heteroscedasticity test is 0.0000, which are less than significant level at 5%. Thus H_0 is rejected and residuals for the model are heteroscedastic.

4.4.2 Serial Correlation

Table 4.6.1(a): Hypothesis for Serial Correlation Test

Hypothesis: $H_0 = \text{Residuals are no serial correlation}$

$$H_1 = \text{Residuals are serial correlation}$$

Table 4.6.1(b): Serial Correlation Analysis

Diagnostic Test	Result	Decision
Serial Correlation Analysis: F- statistics, Probability (P-value): $> \alpha=5\%$	F- statistics= 13.342 P-value = 0.0012	P- value $< 5\%$, therefore, Reject H_0

Source: Own Data Collection via STATA

If the p-value is more than α (5%), the null hypothesis cannot be rejected. To find out if the residuals of Model 1, which uses FEM as its analytical model, are associated, a serial correlation test must be performed. From the result, the p-value obtain from the test is 0.0012, which is lower than significant level at 5%. Thus, reject H_0 , and residuals of model 1 has serial correlation.

4.4.3 Multicollinearity

Table 4.7.1(a): Multicollinearity Analysis

Estimated Model (FEM)		
Variable	VIF	1/VIF
GL	1.88	0.533249
lGDP	1.82	0.549024
CR	1.78	0.561098
EL	1.36	0.736760
IFDI	1.15	0.867825
UR	1.11	0.898505
MEAN VIF	1.52	

Source: Own Data Collection via STATA

VIF values greater than 10, which show high multicollinearity, are frequently seen as problematic. VIF values under 5 are generally considered acceptable, though this can change according to the particular situation and the area of study. Overall, the model's mean VIF of 1.52 provides more evidence that multicollinearity is not a problem. This is positive for the reliability of regression results since it indicates that the independent variables in the regression model do not have a strong correlation with one another.

4.5 Conclusion

In conclusion, based on Panel-Correct Standard Error (PCSE), foreign direct investment and GDP per capita are statistically significant and positive relationship with income inequality.

Chapter 5: Discussion, Conclusion, and Implications

5.0 Introduction

This chapter seeks to give a thorough summary and discussion of the major findings and earlier debates after the data analysis of Chapter 4 is completed. Additionally, this study will highlight the investigation's implications, limitations, recommendations and conclusions.

5.1 Summary on Major Findings

The results of the Fixed Effect Model (FEM) show that there is a significant and inverse association between education level (EL) and income inequality (GINI). There exists a noteworthy significant and positive relationship between the unemployment rate (UR) and income inequality (GINI). However, there is no discernible correlation between

globalization (GL), corruption (CR), gross domestic product per capita (IGDP) and foreign direct investment (FDI) with income inequality (GINI). This is because this model has a standard error.

Accordingly, the Heteroskedasticity Modified Wald test for the diagnostic tests showed that the residuals are heteroskedastic. Based on the Wooldridge Test results for autocorrelation, the residuals have a serial correlation. Additionally, the Multicollinearity Test results show that the residuals do not exhibit multicollinearity problems because mean VIF are fewer than 5.

In order to resolve the standard error issue, the Panel-corrected Standard Error (PCSE) result indicates that there is a strong and positive correlation between gross domestic product per capita (IGDP) and foreign direct investment (IFDI) with income inequality (GINI). Furthermore, there is no discernible correlation between income inequality (GINI) and the following variables which are education level (EL), globalization (GL), corruption (CR) and unemployment rate (UR).

5.2 Discussion on Major Findings

The statistical analysis constantly reveals a substantial correlation between foreign direct investment (IFDI) and income inequality in developing countries. Based on other previous research, the empirical findings verify the existence of a non-linear connection between FDI and income inequality and indicate that FDI tends to intensify income disparity (Lê et al., 2021). Furthermore, the research indicates that the impact of foreign direct investment (FDI) on income inequality varies based on the educational attainment and institutional setup of the host countries.

The regression findings indicate a positive and statistically significant correlation between GDP per capita (IGDP) and income inequality in developing countries. It demonstrates a link that aligns with results from other research. Income disparity is

positively and statistically significantly impacted by GDP per capita (Younsi & Bechtini, 2018). The empirical results confirm Kuznets' inverted U-shaped theory regarding the relationship between GDP per capita, economic growth and income inequality.

Statistical research consistently finds no correlation between income disparity and education level in developing countries. Prior research shows a short-term negative but insignificant relationship between higher education and income inequality (Qazi et al., 2016).

When comparing corruption and income disparity in developing nations, statistical research consistently finds no correlation. Based on other previous research, corruption has a positive relationship with income inequality, but income inequality is not significantly influenced by corruption. Not only that, the significance of the test associated with the direction of causality, "corruption causes inequality," is smaller than the one associated with the relation, "income inequality causes corruption," leading the authors to believe that the number of countries for which corruption causes income inequality is smaller than the number of countries for which inequality causes corruption. Therefore, it shows a not significant relationship between corruption and income inequality.

Statistical research consistently finds no correlation between globalization and income inequality in developing countries. Nevertheless, the effects of globalization become insignificant or even detrimental when they are dependent on several sub-indices of political risk.

5.3 Implication

The findings show that foreign direct investment and GDP per capita has a positive and significant relationship with income inequality. To reduce income inequality, foreign

direct investment and GDP per capita should be decreased. In order to promote a more fair distribution of income, governments should enact regulatory measures to restrict foreign ownership or limit foreign investment in particular industries. Governments can implement such laws to protect developing country industries from foreign domination, allowing local businesses to grow and the country to prosper thereby reducing inequality.

Tax laws can also be used as a tool that would bring favor to domestic companies by implementing tax cuts, while discouraging large foreign investment by taxing foreign-owned corporations more heavily. The end goal of this approach is to hinder the inflow of FDI to boost local economic development combined with possibly more equitable income distribution among the population that would curb income inequality creating a more friendly environment for domestic companies.

For the Kuznets inverted U hypothesis, governments may only occasionally direct lower GDP per capita coped with too much income concentration. As the Kuznets curve postulates, the more developed and urbanized a nation is during its early growth phase, the more income inequality spread is intensified. Therefore, government in such case could in fact use some measures to shift the economy towards a location where the income inequality is falling. Such measures might include specifically aimed policies that are aimed at the contraction of GDP. Thus, short-term maximum income limitations by ascription could be prescribed by governments. In order to prevent the high concentration of income at the top level adjust live-up income restrictions or ratios either inside the companies or through the whole economy.

The outcomes disclose the specific union of GDP per capita, income equality and Foreign Direct Investment. Despite the fact that there is a positive link between the index of these features and income disparity, the proposed remedies comprise of the regulation by means of the limitation and the control of foreign investment and in some cases the reduction of GDP. Creation of such policies is based on two main pillars – economic development on a local level and redistribution of income in a

more balanced way in order to achieve reduced income inequality and provide more business chances for domestic producers. However, unless great care and very extensive assessment of influence are made, it's unlikely for the recommendations to benefit the wider economy.

5.4 Limitations

The challenges of precisely estimating income disparity are intensified by the existence of missing data. This is because incomplete datasets can also distort results, especially if some of the countries or demographic groups are disproportionately impacted by data gaps. To overcome these constraints, it is sometimes necessary to rely on alternate data sources or use statistical techniques to impute missing values, both of them may increase uncertainty.

Moreover, there may be a delay in realizing the whole influence of different variables on income inequality since their impacts may not be immediately apparent. Globalization, foreign direct investment, corruption, GDP per capita, and education levels are just a few examples of variables that can have long-term, complicated effects on how income is distributed. Changes in these variables may gradually alter socioeconomic conditions and therefore affect the dynamics of income gaps in ways that are not immediately noticeable over a selected period of time.

When studying the development of income inequality, researchers need to exercise caution and use sound methods to remove barriers. The effects of temporal dynamics and data limitations can be mitigated through the use of sensitivity studies, validation procedures, and cross-country comparisons. Furthermore, in order to raise awareness of income inequality in developing countries, it is crucial to strengthen measures to open up and upgrade data collection infrastructure. Researchers can assess income disparity by recognizing and addressing these issues, which will help governments adopt smart policy interventions to enhance social development.

5.5 Recommendations

It is recommended that future scholars expand the time horizon, for example to be able to conduct a comprehensive analysis of income inequality events in developing countries. Researchers are able to expand the historical scope to consider major events that may have had an impact on income inequality, such as changes in economic policy, trends in globalization, technological advances and changes to markets caused by the COVID-19 pandemic. The use of larger historical studies can help provide a more thorough understanding of the progression of persistent patterns and variables that influence income inequality.

To enhance the generalizability of the findings, it is recommended to use more diverse countries or regions in research projects, going beyond a few specific countries and not just developing countries. This is because taking a broader perspective provides a more complete understanding of the ways in which different national political, economic and geographical factors influence income inequality in different parts of the world. This is because comparative analysis of economic structures, social policies, different regions and countries with different levels of development can help elucidate the different effects of many variables on income inequality in different regions.

Future research efforts should strive to disentangle the direct causal relationships between various factors and income inequality in developing countries, taking into account concurrent economic transformations. This may include using advanced econometric methods or models to effectively distinguish the different effects of different factors.

5.6 Conclusion

However, the outcomes of the statistical analysis also enlighten us on the very forthcoming relationship among the various socioeconomic factors associated with income gap in those countries. The investigation reveals not only multiple relationships, but they go beyond the certain point into something much more complex.

GDP per capita and FDI are the main trends of the process, which increase income inequality. Significant links such as both negative and increasingly statistically significant between FDI and GDP per capita and income inequality spotlights the need of targeted policy intervention directed at save for the reduction of inequalities. Governments should therefore carry out a thorough assessment of the set of regulations that they will enforce to regulate the flow of FDI internationally and GDP per capita even ultimately leading to less unequal distribution of wealth.

Thirdly, the model utilized in this research study is statistically insignificant for education level, globalization, corruption, or unemployment rate; however, these factors play an important role in determining the socio-economic positions. More research is required to reveal the full picture and better understand the possible long-term consequences of the underlying interactions between these variables.

Thus these discoveries are more crucial to economists, politicians, and investors aiming to relax the existing unequal-sharing of income in the developing world. This can be achieved through policies supporting inclusive growth, regional sectors' strength, and improved education which by default centred on narrowing down income inequality for further strategies.

Moreover, thus, through the rising awareness on how income inequalities are developed and persisted, people will work towards building better inclusive and fair communities in poor countries. Policymaking, research, and making use of this knowledge with other

stakeholders will involve a joint effort to determine the most effective evidence-based strategies that address growth and equity.

It is important to bear in mind the research's limits like inaccuracies in the data or postponing of socio-economic factors. In future research, it may be helpful to go beyond the conventional historical data, include multiple geographic areas, and employ method to uncover the underlying causal links. Specifically, policymakers, academics, and stakeholders must work together to adopt evidence-based measures that support fair income distribution and sustainable economic growth.

References

- Abakumova, J., & Primierova, O. (2018). *Economic growth, globalization and income inequality: the case of Ukraine*.
<https://ekmair.ukma.edu.ua/handle/123456789/15748>
- Abolfazl, S., Nemati, M., & Hosseinidoust, S. E. (2018). The effect of education on income inequality in selected Islamic countries. *International Journal of Asia-Pacific Studies*, 14(2), 61–78. <https://doi.org/10.21315/ijaps2018.14.2.3>
- Ajide, K. B., & Alimi, O. Y. (2021). Income inequality, human capital and terrorism in Africa: Beyond exploratory analytics. *International Economics*, 165, 218–240. <https://doi.org/10.1016/j.inteco.2021.01.003>
- Akpa, A. F., Okafor, V., Osabuohien, E., & Bowale, E. (2024). Financial Development and income Inequality: Direct and indirect transmission mechanisms in Sub-Saharan Africa. *Transnational Corporations Review*, 200048. <https://doi.org/10.1016/j.tncr.2024.200048>
- Alili, M. Z., & Adnett, N. (2018). Did FDI increase wage inequality in transition economies? *International Journal of Social Economics*, 45(9), 1283–1304. <https://doi.org/10.1108/ijse-09-2017-0373>
- Arshed, N., Anwar, A., Kousar, N., & Bukhari, S. (2018). Education Enrollment Level and Income Inequality: A Case of SAARC Economies. *Social Indicators Research*, 140(3), 1211–1224. <https://www.jstor.org/stable/48715060>
- Arshed, N., Ali, A., Hassan, M. S., & Bukhari, S. (2019). Education stock and its implication for income inequality: The case of Asian economies. *Review of*

Development Economics, 23(2), 1050–1066.
<https://doi.org/10.1111/rode.12585>

- Chang, S., Gupta, R., & Miller, S. M. (2016). Causality Between Per Capita Real GDP and Income Inequality in the U.S.: Evidence from a Wavelet Analysis. *Social Indicators Research*, 135(1), 269–289. <https://doi.org/10.1007/s11205-016-1485-0>
- Chu, L. K., & Hoang, D. P. (2020). How does economic complexity influence income inequality? New evidence from international data. *Economic Analysis and Policy*, 68, 44–57. <https://doi.org/10.1016/j.eap.2020.08.004>
- Dabla-Norris, E., Kochhar, K., Suphaphiphat, N., Ricka, F., & Tsounta, E. (2015). Causes and consequences of income inequality. *IMF Staff Discussion Note*, 2015(013), 1. <https://doi.org/10.5089/9781513555188.006>
- Deyshappriya, N. P. (2017). Impact of macroeconomic factors on income inequality and income distribution in Asian countries.
- Dorn, F., Fuest, C., & Potrafke, N. (2018). Globalization and income inequality revisited. *Social Science Research Network*.
<https://doi.org/10.2139/ssrn.3143398>
- Education. (n.d.). UNICEF East Asia and Pacific. <https://www.unicef.org/eap/what-we-do/education>
- Erauskin, I., & Turnovsky, S. J. (2022). International financial integration, the level of development, and income inequality: Some empirical evidence. *International Review of Economics & Finance*, 82, 48–64.
<https://doi.org/10.1016/j.iref.2022.05.013>

- Farny, E. (2016). *Dependency Theory: a useful tool for analyzing global inequalities today?* E-International Relations. <https://www.e-ir.info/2016/11/23/dependency-theory-a-useful-tool-for-analyzing-global-inequalities-today/>
- Hauk, W. R., & Hauk, W. R. (2019). *Globalization and Inequality: Sharing Wealth One of Society's Greatest Challenges*. The Globe Post. <https://theglobepost.com/2019/01/30/globalization-inequality/>
- Huang, K., Sim, N., & Hong, Z. (2020). DOES FDI ACTUALLY AFFECT INCOME INEQUALITY? INSIGHTS FROM 25 YEARS OF RESEARCH. *Journal of Economic Surveys*, 34(3), 630–659. <https://doi.org/10.1111/joes.12373>
- Huynh, C. M. (2021). Foreign direct investment and income inequality: Does institutional quality matter? *Journal of International Trade & Economic Development*, 30(8), 1231–1243. <https://doi.org/10.1080/09638199.2021.1942164>
- Inayati, N. D., Arsyad, L., & Pradipto, R. (2018). The corruption-income inequality trap: A study of Asian countries. Economics Discussion Papers, No. 2018-81, Kiel Institute for the World Economy. <http://www.economics-ejournal.org/economics/discussionpapers/2018-81>
- International Business and Finance (Print)*, 67, 102110. <https://doi.org/10.1016/j.ribaf.2023.102110>

- Jayant Menon. (2021). Embracing technology to tackle Asia's growing digital divide. *East Asia Forum*. <https://eastasiaforum.org/2021/08/24/embracing-technology-to-tackle-asias-growing-digital-divide/>
- Jamil, A. B. M., Law, S. H., Khair-Afham, M., & Trinugroho, I. (2024). Financial inclusion and income inequality in developing countries: The role of aging populations. *Research in*
- Katharina.kiener-Manu. (n.d.). *Anti-Corruption Module 4 Key Issues: Theories that Explain Corruption*. <https://www.unodc.org/e4j/en/anti-corruption/module-4/key-issues/theories-that-explain-corruption.html>
- Kenton, W. (2021). *Corruption Perceptioons Index (CPI): Definition, country rankings*. Investopedia. <https://www.investopedia.com/terms/c/corruption-perception-index.asp>
- Khan, I., Nawaz, Z., & Saeed, B. B. (2021). Does trade openness and FDI reduce inequality? Evidence from South Asia. *International Journal of Finance & Economics*, 26(4), 6459-6470.
- Kholmuminov, S., Kholmuminov, S., & Wright, R. E. (2018). Resource dependence theory analysis of higher education institutions in Uzbekistan. *Higher Education*, 77(1), 59–79. <https://doi.org/10.1007/s10734-018-0261-2>
- Lee, J. W., & Lee, H. (2018). Human capital and income inequality. *Journal of the Asia Pacific Economy*, 23(4), 554–583. <https://doi.org/10.1080/13547860.2018.1515002>
- Lee, C., Lee, C., & Lien, D. (2019). INCOME INEQUALITY, GLOBALIZATION, AND COUNTRY RISK: A CROSS-COUNTRY ANALYSIS. *Technological*

and Economic Development of Economy, 26(2), 379–404.

<https://doi.org/10.3846/tede.2019.11414>

Le, T., Nguyen, C. P., Su, T. D., & Tran-Nam, B. (2020). The Kuznets curve for export diversification and income inequality: Evidence from a global sample.

Economic Analysis and Policy, 65, 21–39.

<https://doi.org/10.1016/j.eap.2019.11.004>

Lê, Q., Anh, Q., Pham, H. C., & Nguyen, T. D. (2021). The impact of foreign direct investment on income inequality in Vietnam. *Economies*, 9(1), 27.

<https://doi.org/10.3390/economies9010027>

Little, W. (2014). *Chapter 16. Education*. Pressbooks.

<https://opentextbc.ca/introductiontosociology/chapter/chapter16-education/>

Munir, K., & Bukhari, M. (2019). Impact of globalization on income inequality in Asian emerging economies. *International Journal of Sociology and Social Policy*, 40(1/2), 44–57. <https://doi.org/10.1108/ijssp-08-2019-0167>

Munro, A. (2024). *Dependency theory | Definition & Facts*. Encyclopedia Britannica.

<https://www.britannica.com/topic/dependency-theory>

Onghena, P. (2023). Mixed methods research synthesis for literature reviews. In

Elsevier eBooks (pp. 655–665). <https://doi.org/10.1016/b978-0-12-818630-5.11066-8>

Policardo, L., & Carrera, E. (2018). Corruption causes inequality, or is it the other way around? An empirical investigation for a panel of countries. *Economic*

Analysis and Policy, 59, 92–102. <https://doi.org/10.1016/j.eap.2018.05.001>

- Policardo, L., Carrera, E. J. S., & Risso, W. A. (2019). Causality between income inequality and corruption in OECD countries. *World Development Perspectives*, 14, 100102. <https://doi.org/10.1016/j.wdp.2019.02.013>
- Qazi, W., Raza, S. A., Jawaid, S. T., & Karim, M. Z. A. (2016). Does expanding higher education reduce income inequality in emerging economy? Evidence from Pakistan. *Studies in Higher Education*, 43(2), 338–358. <https://doi.org/10.1080/03075079.2016.1172305>
- Rahman, M. M., & Alam, K. (2022). Effects of corruption, technological innovation, globalisation, and renewable energy on carbon emissions in Asian countries. *Utilities Policy*, 79, 101448. <https://doi.org/10.1016/j.jup.2022.101448>
- Rehal, V., & Rehal, V. (2024, April 5). Kuznets Inverted-U Hypothesis - SPUR ECONOMICS. *SPUR ECONOMICS - Learn and Excel*. <https://spureconomics.com/kuznets-inverted-u-hypothesis/>
- Ross, S. (2023). *What is the human capital theory and how is it used?* Investopedia. <https://www.investopedia.com/ask/answers/032715/what-human-capital-and-how-it-used.asp>
- Saha, S., Beladi, H., & Kar, S. (2021). Corruption control, shadow economy and income inequality: Evidence from Asia. *Economic Systems*, 45(2), 100774. <https://doi.org/10.1016/j.ecosys.2020.100774>
- Sethi, P., Bhattacharjee, S., Chakrabarti, D., & Tiwari, C. (2021). The impact of globalization and financial development on India's income inequality. *Journal of Policy Modeling*, 43(3), 639–656. <https://doi.org/10.1016/j.jpolmod.2021.01.002>

- Shabnum, S., & Malik, Z. (2023). The impact of inflation and unemployment on income inequality in Pakistan. *Journal of Applied Economics and Business Studies*, 7(1), 119–138. <https://doi.org/10.34260/jaeb.717>
- Sitthiyot, T., & Holasut, K. (2021). A simple method for estimating the Lorenz curve. *Humanities & Social Sciences Communications*, 8(1). <https://doi.org/10.1057/s41599-021-00948-x>
- Soto, G. H., Jardón, C. M., & Martínez-Cobas, X. (2023). FDI and Income Inequality in Tax-Haven Countries: The Relevance of Tax Pressure. *Economic Systems*, 101172. <https://doi.org/10.1016/j.ecosys.2023.101172>
- Statista. (2023). *Gini index worldwide 2020, by country*. <https://www.statista.com/forecasts/1171540/gini-index-by-country>
- Sulemana, I., & Kpienbaareh, D. (2018). An empirical examination of the relationship between income inequality and corruption in Africa. *Economic Analysis and Policy*, 60, 27–42. <https://doi.org/10.1016/j.eap.2018.09.003>
- Team, I. (2022). *Lorenz Curve*. Investopedia. <https://www.investopedia.com/terms/l/lorenz-curve.asp>
- Team, I. (2023). *Variance Inflation Factor (VIF)*. Investopedia. <https://www.investopedia.com/terms/v/variance-inflation-factor.asp>
- Team, I. (2024). *GDP per capita: definition, uses, and highest per country*. Investopedia. <https://www.investopedia.com/terms/p/per-capita-gdp.asp>
- Thompson, D. F. (2018). Theories of institutional corruption. *Annual Review of Political Science*, 21(1), 495–513. <https://doi.org/10.1146/annurev-polisci-120117-110316>

- Transparency International. (2021). *How does corruption shape Asia?* - News.
Transparency.org. <https://www.transparency.org/en/news/how-does-corruption-shape-asia>
- Transparency International. (2021). *Bribery or personal connections?* - News.
Transparency.org. <https://www.transparency.org/en/news/bribery-or-personal-connections>
- Ullah, M. A., & Ahmad, E. (2016). Inequality and Corruption: Evidence from Panel Data. *Forman Journal of Economic Studies*, 12, 1–20.
<https://doi.org/10.32368/fjes.20161201>
- Younsi, M., & Bechtini, M. (2018). Economic growth, financial development, and income inequality in BRICS countries: Does Kuznets' inverted U-Shaped Curve exist? *Journal of the Knowledge Economy*, 11(2), 721–742.
<https://doi.org/10.1007/s13132-018-0569-2>
- Yuldashev, M., Khalikov, U., Nasriddinov, F., Ismailova, N., Kuldasheva, Z., & Ahmad, M. (2023). Impact of foreign direct investment on income inequality: Evidence from selected Asian economies. *PLOS ONE*, 18(2), e0281870.
<https://doi.org/10.1371/journal.pone.0281870>
- Zandi, G., Rehan, R., Hye, Q. M. A., Mubeen, S., & Abbas, S. (2022). Do corruption, inflation and unemployment influence the income inequality of developing Asian countries? *International Journal of Applied Economics, Finance and Accounting*, 14(2), 118–128. <https://doi.org/10.33094/ijaefa.v14i2.688>
- Zhu, X., & Niu, X. (2024). Impact of fintech, mineral resources extraction, and globalization on social inequality: Exploring the role of technology innovation

in G10 economies. *Resources Policy*, 89, 104606.

<https://doi.org/10.1016/j.resourpol.2023.104606>

Appendixes

```
. tsset Code Year
      panel variable:  Code (strongly balanced)
      time variable:  Year, 2015 to 2020
      delta:  1 unit

. generate lFDI = ln(FDI)
(9 missing values generated)

. generate lGDP = ln( GDP )
```

Appendix 1 Correlation Analysis

```
. corr GINI EL CR GL lFDI lGDP UR
(obs=155)
```

	GINI	EL	CR	GL	lFDI	lGDP	UR
GINI	1.0000						
EL	-0.0465	1.0000					
CR	0.1252	0.1875	1.0000				
GL	-0.0721	0.3807	0.5949	1.0000			
lFDI	0.3744	0.0357	0.0306	0.0411	1.0000		
lGDP	0.3798	0.4374	0.4756	0.5133	0.2812	1.0000	
UR	0.1357	0.1058	0.1597	0.0048	-0.1990	-0.0357	1.0000

Appendix 2 Descriptive Analysis

```
. xtsum GINI EL CR GL lFDI lGDP UR
```

Variable		Mean	Std. Dev.	Min	Max	Observations
GINI	overall	37.396	7.599821	24.4	53.9	N = 175
	between		7.544269	25.2	52.46667	n = 33
	within		1.139349	31.16267	41.22933	T-bar = 5.30303
EL	overall	58.45483	19.75822	26.17383	118.8837	N = 185
	between		19.64578	27.19532	110.1943	n = 33
	within		3.450876	43.82504	68.8682	T-bar = 5.60606
CR	overall	40.57071	10.72274	27	74	N = 198
	between		10.62958	28.83333	71.16667	n = 33
	within		2.203865	30.57071	51.40404	T = 6
GL	overall	69.44667	7.865677	53.53	86.86	N = 198
	between		7.886655	56.005	85.695	n = 33
	within		1.117237	63.885	74.32167	T = 6
lFDI	overall	22.03096	1.702768	15.85592	25.84482	N = 189
	between		1.672692	18.95281	25.37505	n = 33
	within		.5233556	18.61009	23.45379	T-bar = 5.72727
lGDP	overall	8.784538	.6393548	7.021679	9.853564	N = 198
	between		.6377549	7.126997	9.772801	n = 33
	within		.1112044	8.46449	9.063925	T = 6
UR	overall	7.907071	4.847962	.6	26.43	N = 198
	between		4.642886	.785	21.44667	n = 33
	within		1.579068	3.010404	15.38174	T = 6

Appendix 3 Pooled Ordinary Least Square (POLS)

```
. reg GINI EL CR GL lFDI lGDP UR
```

Source	SS	df	MS	Number of obs	=	155
Model	3343.44659	6	557.241098	F(6, 148)	=	15.05
Residual	5479.62889	148	37.0245196	Prob > F	=	0.0000
Total	8823.07548	154	57.2926979	R-squared	=	0.3789
				Adj R-squared	=	0.3538
				Root MSE	=	6.0848

GINI	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
EL	-.0803668	.0296029	-2.71	0.007	-.1388657	-.0218679
CR	.0356938	.0619311	0.58	0.565	-.0866896	.1580772
GL	-.2951474	.0845791	-3.49	0.001	-.462286	-.1280088
lFDI	1.296814	.312372	4.15	0.000	.6795283	1.914099
lGDP	6.581481	1.082381	6.08	0.000	4.442564	8.720398
UR	.3658256	.109999	3.33	0.001	.1484541	.5831972
_cons	-28.08351	9.386141	-2.99	0.003	-46.63167	-9.535345

Appendix 4 Random Effect Model (REM)

```
. xtreg GINI EL CR GL lFDI lGDP UR, re
```

```
Random-effects GLS regression              Number of obs   =       155
Group variable: Code                      Number of groups =        33

R-sq:                                     Obs per group:
      within = 0.2234                               min =          1
      between = 0.0825                               avg  =         4.7
      overall = 0.1345                               max  =          6

Wald chi2(6) =       35.47
corr(u_i, X) = 0 (assumed)                  Prob > chi2      =       0.0000
```

GINI	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
EL	-.0442019	.0280439	-1.58	0.115	-.0991668	.010763
CR	-.0273032	.0448015	-0.61	0.542	-.1151125	.0605061
GL	-.1111579	.0836719	-1.33	0.184	-.2751519	.0528361
lFDI	.4223867	.2099056	2.01	0.044	.0109793	.833794
lGDP	.9706458	.9355081	1.04	0.299	-.8629163	2.804208
UR	.4173473	.0807815	5.17	0.000	.2590185	.5756761
_cons	27.69796	10.56696	2.62	0.009	6.987109	48.40882

sigma_u	6.6008923	
sigma_e	1.1837538	
rho	.96884194	(fraction of variance due to u_i)

Appendix 5 Breusch and Pagan Lagrangian Multiplier Test for Random Effects

```
. xttest0
```

```
Breusch and Pagan Lagrangian multiplier test for random effects
```

```
GINI[Code,t] = Xb + u[Code] + e[Code,t]
```

```
Estimated results:
```

```
|          Var          sd = sqrt(Var)
```

```

-----+-----
GINI |      57.2927      7.569194
e |      1.401273      1.183754
u |      43.57178      6.600892

```

```

Test:   Var(u) = 0
        chibar2(01) =    234.52
        Prob > chibar2 =    0.0000

```

Appendix 6 Fixed Effect Model (FEM)

```
. xtreg GINI EL CR GL lFDI lGDP UR, fe
```

```

Fixed-effects (within) regression           Number of obs   =        155
Group variable: Code                       Number of groups  =         33

R-sq:                                     Obs per group:
    within = 0.2453                                min =          1
    between = 0.0004                                avg  =         4.7
    overall = 0.0130                                max  =          6

                                         F(6,116)         =        6.28
corr(u_i, Xb) = -0.2548                     Prob > F         =       0.0000

```

```

-----+-----
GINI |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----+-----
EL |    -.05875   .0300448    -1.96   0.053   -1.182575   .0007575
CR |   -.0605061  .0466146    -1.30   0.197   -1.1528321  .0318199
GL |   -.1397655  .0937169    -1.49   0.139   -.3253836   .0458527
lFDI | .2802527   .2123221     1.32   0.189   -.140278    .7007834
lGDP | -.591855    1.040061    -0.57   0.570   -2.651828   1.468118
UR |   .3619088   .0848383     4.27   0.000   .1938758    .5299418
_cons | 49.10549    12.8983     3.81   0.000   23.55879    74.65219
-----+-----
sigma_u | 8.046218
sigma_e | 1.1837538
rho | .97881446   (fraction of variance due to u_i)
-----+-----
F test that all u_i=0: F(32, 116) = 118.58             Prob > F = 0.0000

```

Appendix 7 Hausman Test

```
. est store random
. hausman fixed random
```

```

-----+-----
      Coefficients
      (b)      (B)      (b-B)      sqrt(diag(V_b-V_B))
      fixed    random    Difference      S.E.
-----+-----
EL |    -.05875   -.0442019   -.0145481   .0107811
CR |   -.0605061  -.0273032   -.0332029   .0128741
GL |   -.1397655  -.1111579   -.0286076   .0422122
lFDI | .2802527   .4223867   -.142134   .0319427
lGDP | -.591855    .9706458   -1.562501   .4544805
UR |   .3619088   .4173473   -.0554385   .0259209
-----+-----

```

```

b = consistent under Ho and Ha; obtained from xtreg
B = inconsistent under Ha, efficient under Ho; obtained from xtreg

```

```
Test:   Ho:   difference in coefficients not systematic
```

```

chi2(6) = (b-B)' [(V_b-V_B)^(-1)] (b-B)
        =      31.73
Prob>chi2 =      0.0000
(V_b-V_B is not positive definite)

```

Appendix 8 Variance Inflation Factor (VIF)

```
. vif
```

Variable	VIF	1/VIF
GL	1.88	0.533249
lGDP	1.82	0.549024
CR	1.78	0.561098
EL	1.36	0.736760
lFDI	1.15	0.867825
UR	1.11	0.898505
Mean VIF	1.52	

Appendix 9 Heteroskedasticity

```
. xttest3
```

Modified Wald test for groupwise heteroskedasticity
in fixed effect regression model

H0: $\sigma(i)^2 = \sigma^2$ for all i

chi2 (33) = 2.6e+30
Prob>chi2 = 0.0000

Appendix 10 Autocorrelation

```
. xtserial GINI EL CR GL lFDI lGDP UR
```

Wooldridge test for autocorrelation in panel data

H0: no first order autocorrelation

F(1, 25) = 13.342
Prob > F = 0.0012

Appendix 11 Cluster Code for POLS

```
. reg GINI EL CR GL lFDI lGDP UR,cluster ( Code )
```

Linear regression	Number of obs	=	155
	F(6, 32)	=	4.60
	Prob > F	=	0.0018
	R-squared	=	0.3789
	Root MSE	=	6.0848

(Std. Err. adjusted for 33 clusters in Code)

	GINI	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
EL		-.0803668	.0641359	-1.25	0.219	-.2110075 .0502738
CR		.0356938	.105976	0.34	0.738	-.1801723 .2515599
GL		-.2951474	.2187195	-1.35	0.187	-.7406644 .1503696
lFDI		1.296814	.5543576	2.34	0.026	.1676241 2.426003
lGDP		6.581481	1.847866	3.56	0.001	2.817501 10.34546
UR		.3658256	.1885121	1.94	0.061	-.0181609 .7498122
_cons		-28.08351	20.23026	-1.39	0.175	-69.29119 13.12418